POLLUTANT EXPOSURE STUDIES OF EMERGING MODES OF TRANSPORTATION

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POLLUTANT EXPOSURE STUDIES OF EMERGING MODES OF TRANSPORTATION

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To my dearest friends and roommates of the Yellow House.

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LIST OF SYMBOLS AND ABBREVIATIONS

ADA	The Americans with Disabilities Act
CAR-TEEH	Center for Advancing Research in Transportation Emissions, Energy, and Health
EPA	Environmental Protection Agency
FC	Functional Classification
GAO	Government Accountability Office
GDOT	Georgia Department of Transportation
MARTA	Metropolitan Atlanta Rapid Transit Authority
NOAA	National Oceanic and Atmospheric Administration
PAPS	Personal Air Pollution Sensors
PM	Particulate Matter
OST-R	Office of Research and Technology
UTC	University Transportation Center
US	United States
WHO	World Health Organization

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SUMMARY

The Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH) has invested in exposure studies and other similar initiatives that focus on the impact of transportation emissions on human health. CARTEEH's research program includes a collaborative program that funds joint projects conducted by consortium members and competitive programs. Two of the funded projects led by the Georgia Institute of Technology include a paratransit transport exposure study and an urban cyclist exposure study.

The work presented in this thesis includes the experimental procedures and findings from the paratransit exposure study and urban cyclist exposure study, accompanied by a literature review. The literature review consists of four main topics: (1) adverse health effects from particulate matter (PM) exposure, (2) factors that affect air quality and contribute to varying particulate concentrations, (3) methodologies for measuring human exposure to PM for different modes of transportation, and (4) an overview of low-cost air quality sensors.

The findings from these initial experiments confirm the impact of transportation networks and the design of associated infrastructure on users' health. Users' health is negatively impacted by prolonged or repetitive exposure to particulate matter. These studies are the initial step to characterize the particulate matter exposure of paratransit and cycling in urban environments. Understanding users' exposure is the first step to identify strategies to reduce exposure to harmful pollutants.

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CHAPTER 1. INTRODUCTION

Transportation planners and engineers provide effective transportation options by accommodating the needs of users. Demand, cost, accessibility, safety, and comfort are all given substantial consideration (Farrell, et al., 2015). However, some needs are neglected in the planning process, such as the development of transportation networks typically taking place without any consideration of users' exposure to harmful pollutants. Pollutant exposure can significantly impact people with heart or lung diseases, people with diabetes, older adults, and children less than 18 years old (U.S. Environmental Protection Agency, 2017). Many individuals sensitive to pollutant exposure are reliant on public transportation and active transportation to complete necessary travel, due to additional age and/or mobility restrictions. During transport, individuals may be unknowingly exposed to large quantities of pollutants. Prolonged or repetitive exposure to particulate matter can negatively impact the health of users.

There are many consequences associated with exposure to high levels of particulate matter. Health effects from significant exposure to particles with an aerodynamic diameter of 2.5 micrometers or smaller ($PM_{2.5}$) include respiratory illnesses, cardiovascular disease, and cerebrovascular disease. The Environmental Protection Agency (EPA) also attributes particle pollution to other health problems including reduced lung function, asthma, heart attack, and stroke (U.S. Environmental Protection Agency, 2017). The World Health Organization ranks air pollution from particulate matter as the thirteenth most prominent cause of death worldwide (World Health Organization, 2002). An estimated 800,000 premature deaths occur annually according to a study from the *Journal of Medical Toxicology* (Anderson et al., 2012).

Pollutant exposure studies are the preliminary step to better understand the hazardous pollutant exposure of different modes of transportation. These studies monitor concentrations of pollutants during transport and report any notable patterns. The patterns found in the pollutant exposure studies can be used to identify strategies to reduce exposure or to recommend routes or time of day for healthier travel.

For some modes of transportation, such as paratransit transport and cycling, little is known about users' particulate matter exposures. This understanding is essential to provide safe transportation options for some of the most vulnerable populations.

1.1 Center for Advancing Research in Transportation Emissions, Energy, and Health

The Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH) has invested in exposure studies and other similar initiatives that focus on the impact of transportation emissions on human health. CARTEEH is a Tier-1 center, funded by the U.S. Department of Transportation's Office of the Secretary for Research and Technology (OST-R) under the University Transportation Centers (UTC) program. The center is composed of professionals and students from the Texas A&M Transportation Institute, Johns Hopkins University, Georgia Institute of Technology, University of Texas at El Paso, and the University of California, Riverside. In addition to furthering transportation emissions research, CARTEEH promotes interdisciplinary collaboration between the transportation and public health sectors (CARTEEH, 2019).

CARTEEH's research program includes a collaborative program that funds joint projects conducted by consortium members and competitive programs (CARTEEH, 2019). The funded projects were selected for their multimodal and interdisciplinary nature. Two of the funded projects led by the Georgia Institute of Technology include a paratransit transport exposure study and an urban cyclist exposure study.

1.2 Monitoring In-cabin Particulate Matter Exposure during Paratransit Transport

The first CARTEEH project led by the Georgia Institute of Technology is a feasibility study of monitoring in-cabin pollutant exposure during paratransit transport. Paratransit transport provides mobility options for seniors and individuals that cannot access fixed route bus or rail services.

As the population of the United States ages, it is imperative that engineers and planners provide safe transportation options for seniors. Residents age 65 and older are expected to comprise 19% of the national population by 2030 (Vicent & Velkoff, 2010). A significant portion of this population has limited access to transportation options and utilizes services, such as paratransit transport (Rosenbloom, 2007). The Government Accountability Office reported a 7% increase in annual paratransit trips from 2007 to 2010 (U.S. Government Accountability Office, 2012). The increase in senior population will likely lead to more trips by paratransit operators and increased exposure to particulate matter emissions. Additionally, senior populations are more susceptible to chronic diseases caused by repetitive or prolonged exposure to such emissions (Simoni, et al., 2015).

Air pollutant exposure during the use of paratransit services is understudied. Due to different operating characteristics than typical fixed route bus systems, paratransit transport may expose passengers to greater quantities of pollutants. Paratransit operations have longer ingress and egress times that lead to longer idling times. This experiment is designed as a screening study to identify the needs for additional measurements and analysis.

1.3 Measuring Particulate Matter Exposure of Urban Cyclists Using an Instrumented Bicycle

The second CARTEEH project is an air pollutant exposure study of urban cyclists. Increased cycling can make direct and indirect contributions toward addressing both the health concerns arising from sedentary lifestyles and other societal transportation issues including congestion, environmental, and equity problems (World Health Organization, 2002). However, in the process of cycling for transportation, cyclists are exposed to pollutants that could adversely impact their health. Although it has been found that the health benefits of cycling on an individual basis outweigh air pollution and safety impacts, researchers in the Netherlands found that pollutant exposure during a typical trip can be almost double depending on the mode of transport and specific route (Zuurbier, et al., 2010).

This study is an initial experiment to access the feasibility of using an instrumented bicycle equipped with low-cost air quality sensors to monitor the $PM_{2.5}$ exposure of cyclists in Atlanta, Georgia. Pollutant exposure is not taken into consideration during the development of cycling networks. This lack of consideration is due to limited understanding of which types of cycling infrastructure may be better or worse for cyclists' health based on exposure to air pollutants. This study seeks to identify preliminary patterns about cyclists' exposure based on available route characteristics, such as type of cycling infrastructure.

Both CARTEEH projects seek to increase the understanding of the impact of transportation emissions on human health. This understanding can be used to shape future studies and to develop necessary guidelines to protect users from harmful pollutant exposure. The work presented in this thesis includes the experimental procedures and findings from the paratransit exposure study and urban cyclist exposure study, accompanied by a literature review. The literature review consists of four main topics: (1) adverse health effects from particulate matter (PM) exposure, (2) factors that affect air quality and contribute to varying particulate concentrations, (3) methodologies for measuring human exposure to PM for different modes of transportation, and (4) an overview of low-cost air quality sensors.

The findings from these initial experiments confirm the impact of transportation networks and the design of associated infrastructure on users' health. Users' health is negatively impacted by prolonged or repetitive exposure to particulate matter. These studies are the initial step to characterize the particulate matter exposure of paratransit and cycling in urban environments.

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CHAPTER 2. LITERATURE REVIEW

The literature review consists of four main topics: (1) adverse health effects from particulate matter (PM) exposure, (2) factors that affect air quality and contribute to varying particulate concentrations, (3) methodologies for measuring human exposure to PM for different modes of transportation, and (4) an overview of low-cost air quality sensors. The findings from the literature review suggest it is necessary to control for certain meteorological factors and roadway characteristics. Approaches to measuring PM exposure were also documented, which were used as references in developing data analysis parameters and methodologies for these studies.

2.1 Adverse Health Effects from Particulate Matter Exposure

Pollutant concentrations in the air increase as vehicle activity increases (Schweitzer & Zhou, 2010). The attraction of vehicular traffic to a region can be a sign of economic development. However, there are many consequences associated with exposure to high levels of particulate matter. Repetitive or prolonged exposure to fine particulate matter result in negative health effects including respiratory illnesses, cardiovascular disease, and cerebrovascular disease. In addition to these health effects, the United States Environmental Protection Agency also attributes particle pollution to other health problems including reduced lung function, asthma, heart attacks, and stroke (U.S. Environmental Protection Agency, 2015).

The World Health Organization ranks air pollution from particulate matter as the thirteenth most prominent cause of death worldwide (World Health Organization, 2002). 80,000 premature deaths annually result from air pollution (Anderson, et al., 2012).

Particles with a diameter of 2.5 micrometers or smaller are the most harmful to human health. Fine inhalable particles can infiltrate deep into the lungs and enter the bloodstream (U.S. Environmental Protection Agency, 2018).

As part of the Air Pollution and Health: a European Approach (APHEA) study, daily particulate concentrations and number of deaths were observed for twelve European cities. Cities that experienced an increase of 50 $\mu g/m^3$ in particulate matter correlated with a 2% increase in daily mortality (Katsouyanni, et al., 1997).

The severity of the health impacts depends on the amount of time an individual is exposed to elevated pollutant concentrations. Pollutant exposure is a critical consideration when planning for active modes of transportation, because trips by bicycle or by foot usually take longer than trips by other modes of transportation. Additionally, cyclists and pedestrians have increased inhalation rates. Inhalation rates represent the volume of air inhaled over a specified timeframe (U.S. Environmental Protection Agency, 2018). Dutch researchers found that cyclists' inhalation rates were on average 2.1 times higher than car passengers' inhalation rates (Zuurbier, et al., 20019). Increased inhalation rates result in increased volumes of inhaled pollutants that can adversely impact the health of cyclists.

Some researchers have linked urban planning methodologies to poor air quality. Lawrence Frank and Peter Engelke from the University of British Columbia and Georgetown University, respectively, claimed that urban sprawl discourages active modes of transportation, such as walking and cycling (Frank & Engelke, 2005). In contrast, developing more dense urban environments increases congestion and centralizes harmful vehicle emissions (Frank & Engelke, 2005). Dense urban environments and proximity to high traffic corridors can negatively impact the health of city residents when only considering pollutant exposure. However, other studies have shown that increased residential densities and improved street connectivity are associated with health benefits, such as reductions in the odds of being overweight and/or obese (Bodea, et al., 2009).

A study published by the *American Journal of Respiratory and Critical Care Medicine* examined the patterns between respiratory symptoms in school aged students and proximity to vehicular traffic. Traffic-related pollutant measurements were taken in ten schools near high traffic roadways in the San Francisco Bay Area. Bronchitis symptoms and physician-diagnosed asthma were greater in neighborhoods with higher concentrations of pollutants from vehicular traffic (Kim, et al., 2004). These findings pose environmental justice concerns, because low-income and minority children are disproportionately assigned to schools with poor air quality. Pollutant concentrations were significantly higher in schools and in the surroundings of schools with higher percentages of African American, Latino, and Asian students (Grineski & Collins, 2018).

The findings presented in the literature emphasize the hazards of repetitive and prolonged exposure to particulate matter, specifically air pollutants associated with vehicular traffic. Exposure has serious consequences for many urban residents including people with heart or lung diseases, people with diabetes, older adults, and children less than 18 years old. The large portion of the population subject to these adverse health impacts confirms the importance of considering air pollutant exposure in the development of transportation networks.

2.2 Factors that Affect Pollutant Concentrations

Studies included in this literature review indicate that particulate matter concentrations are impacted by meteorological factors including temperature, relative humidity, sun exposure, precipitation, wind speed, and wind direction. Additionally, the literature suggested that particulate matter concentrations are impacted by roadway characteristics including traffic volumes, traffic speed, and monitor distance from roadway. Other factors including land use and presence of vegetation and green space may need to be considered.

2.2.1 Meteorological Factors

Air quality can be highly variable over a short timespan due to weather conditions. There are fewer poor air quality days during winter. However, there is the risk that cold temperatures and stagnant air can result in inversions. Inversions trap pollutants in the stagnant air close to the ground and create poor air quality during the winter. Inversion layers or the rapid cooling of air as the atmospheric height increases trap contaminants amongst the urban topography. The warm upper layer of the atmosphere acts as a lid and prevents the pollutants from dispersing (Fort Air Partnership, 2015).

The effects of inversion layers were examined in a mobile air quality measurement study conducted by the Canadian Regional and Urban Investigation System for Environmental Research in Montreal, Quebec. The objectives of the study were to understand how pollutants vary seasonally and spatially across different neighborhoods in Montreal (Levy, et al., 2013). Researchers measured pollutant concentrations of two routes for 34 days and calculated the average concentration of the roadway segment for the year and for each season. It was observed that higher mean concentrations occurred during the winter months due to greater build-up of pollutants from reduced evaporation (Levy, et al., 2013).

Higher humidity or increased amounts of water vapor in the air also impacts air quality. Water molecules bind with corrosive gases and form acid solutions. The bonds are facilitated by the small size and polar nature of water molecules. These acid solutions are extremely harmful to human health and can also cause property damage. Relative humidity is generally higher in the summer and as a result there are more days in the summer with poor air quality (Wolkoff, 2018).

The presence of sun facilitates chemical reactions between pollutants resulting in smog. Precipitation cleans the air and washes away water-soluble pollutants, therefore, days with precipitation and days following heavy precipitation generally have lower pollutant and particulate concentrations (National Oceanic and Atmospheric Administration, 2017).

Wind is one of the most impactful meteorological factors. High speed winds cause pollutants to disperse far from the original source. Higher winds are generally associated with better air quality, because the concentration of particulates is less dense near the source (Vallero, 2014).

Wind direction also impacts the air quality of a region. Areas downwind from a pollutant source will experience worse air quality, because the pollutants are being blown from the source (Vallero, 2014). A study published by the *Air Quality, Atmosphere & Health* recommended collecting upwind and background air quality measurements due to the effects of wind speed and direction on the dispersion of particulates. It is important to collect background concentrations, because wind generated by high speed vehicles can cause pollutants to travel 50 to 100 meters upwind from the emission source (Baldauf, et al., 2009).

In conclusion, other air quality exposure studies have controlled for temperature, relative humidity, wind speed, and wind direction. Other studies using instrumented vehicles have also used GPS data in conjunction with sensors that monitor meteorological factors to record the routes traveled. The literature confirms the need to control for these factors, because meteorology can vary both temporally and spatially.

2.2.2 Traffic Characteristics

Many studies have been conducted to understand the influence of roadway characteristics, such as traffic volumes, traffic speed, and monitor distance from the roadway on a region's air quality. Studies have shown that pollutant concentrations in the air increase as vehicle activity increases (Schweitzer & Zhou, 2010). Scientists from the Institute of Environmental Assessment and Water Research (IDAEA-CSIC) found that particulate matter values were greatest in the morning when traffic flow began. The particulate matter levels then decreased gradually throughout the day due to increased boundary layer and increased wind speeds (Pérez, et al., 2010).

Other factors, such as nearby construction, increased the particulate matter concentrations at the monitoring site in Barcelona, Spain (Pérez, et al., 2010). Additionally, the Canadian Regional and Urban Investigation System for Environmental Research found that neighborhoods that had more identifiable sources of pollutants had higher mean concentrations of all pollutants. For example, the Anjou neighborhood of Montreal that is close to two major highways and a major interchange had higher pollutant concentrations than the other studied neighborhoods (Levy, et al., 2013).

Another neighborhood monitoring study was completed by researchers from Harvard University for the Mission Hill Neighborhood of Boston, Massachusetts. The results of the study published in the *American Journal of Public Health* found that roadway speed correlated with the type of pollutants emitted. Vehicles traveling at speeds of 15 miles per hour or less emitted ultrafine particulates, whereas vehicles traveling at higher speeds emitted more $PM_{2.5}$. It is important to note that this study was completed in 2009 and in the past decade the fleet composition has changed, possibly changing the results of this study. The researchers from this study recommended that future work examine patterns between pollutant concentrations and the distance from the monitor to roadway (Buonocroe, et al., 2009).

Some researchers have examined the effects of monitor distance from the roadway. Richard Baldauf, a leading air quality specialist for the U.S. Environmental Protection Agency (2009) published a study in *Air Quality, Atmosphere & Health* that described the factors that affect the collection and interpretation of pollutant concentrations. To ensure continuity in data collection, Baldauf, et al. recommended that monitors are placed equal distance from the roadway. As expected, particulate concentrations decrease exponentially when moved further from the roadway. However, other characteristics, such as roadway curvature, roadway configuration, and meteorology can also be responsible for these decreases. Another monitoring option is to use instrumented vehicles to understand how pollutant concentrations change along a corridor (Baldauf, et al., 2009).

Baldauf, et al. (2013) conducted another study to understand how changing roadway configuration impacts pollutant concentrations. This study combined results from fixed-site and mobile air quality monitors. Higher peak concentrations were recorded along at-grade locations. Concentrations at-grade were also greatly impacted by vehicle activity. In comparison, concentrations recorded at the top of the cut section were 15 to 25 percent lower than the at-grade concentrations. The authors also recommend that the presence of buildings and other structures be considered when monitoring near-road air quality (Baldauf, et al., 2013).

The findings from previous studies show that air quality is correlated with vehicular traffic patterns and roadway configuration. These characteristics are important to consider when drawing conclusions about an area's air quality. Air quality is impacted by the pollutant emissions of vehicles, but there are also other built environment factors that impact air quality.

2.2.3 Built Environment Factors

Though vehicles contribute greatly to pollutant emissions, there are other factors that also impact urban air quality. Air quality can be correlated to land use. Land uses that host businesses, specifically restaurants, emit more pollutants than other establishments. Researchers from Carnegie Mellon University found greatly elevated particulate matter concentrations in the vicinity of numerous restaurants and commercial districts containing restaurants (Robinson, et al., 2018). Other businesses, such as dry cleaners, have also been recognized as sources of high pollutant emissions (Schreiber, et al., 1993). Pollutants emitted from these businesses and emissions from surrounding industrial areas contribute to “hot spots” or areas of elevated exposure observed during mobile air quality monitoring (California Air Resources Board, 2019).

Another factor impacting air quality is the presence of vegetation and green space. Roadside vegetation affects nearby air quality as shown by research conducted by the Environmental Protection Agency. The agency recommends vegetation barriers with a height of 5 meters or more and with a width of 10 meters or more to remove particulates and enhance dispersion (Baldauf, 2017). There are very few roadways in urban environments that have vegetation with such physical characteristics. Green space, however, is more prevalent in cities. Urban green space of all scales has been shown to reduce air pollution (Zupancic, et al., 2015). The presence of trees is also a crucial factor. The National Recreation and Parks Association estimates that urban park trees in the United States remove 75,000 tons of pollutants annually, or 80 pounds per acre of tree cover (Nowak & Heisler, 2010). Lower particulate concentrations observed in parks or along multi-use trails may be partially attributed to the presence of trees.

There are many factors that affect air quality. These factors are important to consider when drawing conclusions about an area’s air quality. Air quality is impacted by meteorological factors, roadway characteristics, and built environment factors. Studies seeking to monitor pollutant exposure should consider the impact of these factors and take the necessary steps to control for these variables when possible.

2.3 Pollutant Exposure Studies of Different Modes of Transportation

Many studies have been conducted to understand the impacts of transportation on air quality. The motivation for these studies stems from the enormous environmental impacts from transportation. Transportation accounts for approximately 30 percent of pollutant emissions in the United States (U.S. Environmental Protection Agency, 2019). Though there have been many studies to monitor the overall impacts of different modes of transportation on air quality, there have been far fewer studies that examine the pollutant exposure of individuals during transport. The findings from monitoring pollutant exposure during transport can be used to identify strategies to reduce exposure or to recommend routes or time of day for healthier travel.

Both paratransit transport and cycling, the focuses of pollutant exposure studies funded by CARTEEH, are understudied. However, there are some existing studies that have measured exposure to particulate matter related to these two modes. These approaches were used as references in developing data analysis parameters and methodologies for the CARTEEH projects.

2.3.1 Exposure Studies of Paratransit Transport

Pollutant exposure during paratransit transport is understudied. Though there is no literature specific to paratransit transport, there have been studies that monitored pollutant exposure during transport by city bus and by school bus. However, the operating characteristics of paratransit transport differ from those of traditional transit services. Paratransit operations have longer ingress and egress times to allow passengers that require assistance to board and exit the vehicle that lead to longer idling times.

Though paratransit transport has different operating characteristics, the exposure studies of city bus and school bus have applicable methodologies. Some cities have completed comprehensive $PM_{2.5}$ personal exposure studies of all transportation users. These studies compare the exposure of many different modes of transportation. For example, researchers from the Imperial College of Science Technology and Medicine measured personal exposure levels for trips taken by bicycle, bus, car, and underground rail in London (Adams, et al., 2001). Many other cities have completed similar studies; however, paratransit transport monitoring has not been included in any of these studies.

Many of the comprehensive studies also excluded transport by school bus. Of the available modes of transportation, school buses have the most similar operating characteristics to paratransit transport. Like paratransit transport, transport by school bus has long periods of idling and frequent stops. School buses also transport children that are vulnerable to air pollution like many of the passengers of paratransit transport.

There have been a few studies that monitored children’s exposure to diesel exhaust on school buses. Researchers from the University of California Los Angeles measured self-pollution in school buses using a tracer gas technique and found that only 0.3% of air inside the cabin was from the bus's own exhaust (Behrentz, et al., 2004). Diesel exhaust has highly concentrated amounts of fine particles. Repetitive exposure to fine particles, such as $PM_{2.5}$ has been shown to increase respiratory illnesses in children (Behrentz, et al., 2004).

Similar studies that measured diesel exhaust exposure on school buses found that students' exposure was five to ten times higher than exposure at fixed monitoring sites and inside personal vehicles (Solomon, et al., 2001; Sabin, et al., 2005). Additionally, certain conditions resulted in increased students' exposure. Heightened exposure was observed when the bus was idling with the windows opened, when driving typical routes with the windows closed, and when traveling through areas of high traffic (Solomon, et al., 2001). The effect of traffic along the route was shown in other studies. An environmental justice project conducted by the University of Maryland found that students commuting by bus through Baltimore, Maryland's central business district were exposed to the highest levels of pollutants (Wu, et al., 1998).

The lack of current literature available about pollutant exposure during paratransit transport confirms the need for such studies. The available studies of transport by city bus and by school bus show that particulate matter concentrations are greater in the cabin of buses than the pollutant exposure of other modes of transportation (Solomon, et al., 2001). Factors, such as opened or closed windows, duration of idling, and traffic conditions along routes were found to impact exposure. Concentrations were not studied in relation to when the vehicles' doors were opened or closed. The doors of both buses and paratransit vehicles open frequently to accommodate stops and this characteristic may impact the pollutant exposure of passengers.

2.3.2 Exposure Studies of Cyclists

Exposure studies of cyclists are prominent in Europe. European studies have used personal monitoring devices or an instrumented bicycle to measure cyclists' exposure. Cyclists' exposure has been compared to that of other modes of transportation in some recent studies. Though cycling does not emit any pollutants, cyclists still risk exposure to particulate matter, because cycling facilities are frequently located near motorized vehicle infrastructure.

Researchers from the Finnish National Institute for Health and Welfare used portable air quality monitoring devices to collect particulate matter concentrations along popular cycling routes in Helsinki, Finland; Rotterdam, Netherlands; and Thessaloniki, Greece and found active transportation commuters are at risk of higher air pollution exposure than car users (Okokon, et al., 2017). Studies with similar findings used instrumented bicycles to monitor cyclists' pollutant exposure. A notable development is the Aeroflex®. The Aeroflex® developed by the Flemish Institute for Technological Research and Ghent University, Department of Information Technology is an instrumented bicycle equipped with a GRIMM® 1.108 to record particulate matter concentrations (Elen, et al., 2012). In addition to the GRIMM® 1.108, the Aeroflex® has temperature and relative humidity monitors.

The Aeroflex® has been used as a mobile air quality monitor in Antwerp, Gent, Brussels, and other cities in Belgium (Elen et al., 2012). An experiment from VITO

(Flemish Institute for Technological Research) used the Aeroflex® for mobile monitoring of ultrafine particles, $PM_{2.5}$, and black carbon. The technical approach of the study was to monitor multiple runs of a fixed route over the course of 10 days. Over the course of the study, researchers documented the date, start and end time of the run, duration of run, temperature, wind direction, and relative humidity during each run. Researchers also recorded background concentration from a fixed monitor. Because urban air quality is a combination of many local sources, the study subtracted the background concentration from the collected concentrations. The use of background correction showed a faster convergence towards a representative concentration and reduced the number of runs needed to produce representative results for $PM_{2.5}$ (Van Poppel, et al., 2013) (Lenschow, et al., 2001). However, single point background concentrations may not be the most representative of the urban background concentration, because concentrations vary considerably in space and time.

To analyze the collected data, researchers divided the route into different zones based on vehicle speed and distance from vehicle traffic. For example, Zone 1 had traffic traveling at 70 kilometers per hour with approximately 10,000 vehicles per day on the roadway. The zones were also determined by considering the presence of bicycle infrastructure. The relationship between the presence of bicycle infrastructure and $PM_{2.5}$ concentrations was not examined in this study, however the mobile measurements collected in this study confirmed the spatial variability of air pollution (Van Poppel, et al., 2013).

In addition to experiments using the Aeroflex®, Flemish researchers from VITO and IMOB (Transportation Research Board) have conducted studies about pollutant exposure in traffic. Dons et al. (2013) used portable aethalometers, global positioning systems (GPS), and travel diaries to compare the black carbon exposure of more than 1,500 trips in Flanders, Belgium. The collected data from these trips showed that characteristics of the surrounding environment greatly impact an individual's exposure. Individual's exposure while traveling on highways (10.7 $\mu g/m^3$) and on urban roads (9.6 $\mu g/m^3$) was much larger than when traveling on rural roads (6.1 $\mu g/m^3$) (Dons, et al., 2013).

Panis, et al. (2010) from VITO measured $PM_{2.5}$ and PM_{10} concentrations and ventilatory parameters of cyclists and car passengers in three Belgium cities and found that quantities of particulates inhaled while cycling were 400 to 900 percent higher than while riding in a car. The study indicated that there are three factors that prevent accurate comparison between the exposure of cyclists and passengers. The factors are (1) breathing frequency is much greater when cycling, (2) the number of particulates that remains in the respiratory tract increase while exercising, and (3) the cycling trip takes longer to complete (Panis, et al., 2010).

Dutch researchers are also leaders in research pertaining to the health benefits and safety of cycling. The first publication that monitored the air quality of non-motorized modes of transportation was completed in Amsterdam. The study used personal monitor devices to measure pollutant exposure of cyclists, car drivers, and pedestrians. The researchers monitored four routes: two urban routes, one route including a tunnel on a busy highway, and one rural route south of Amsterdam and found that the readings from the personal monitor devices were higher for car drivers than for cyclists (van Wijnen, et al., 1995). This finding is contradictory to findings from more recent studies that found cyclists have higher pollutant exposure due to longer travel times and higher frequency of inhalation (De Hartog, et al., 2010).

Additionally, De Hartog, et al. (2010) from the University of Utrecht and the Netherlands Environmental Assessment Agency found that the health benefits of cycling were greater than the risks of cycling compared to those of driving a private vehicle. The researchers complied results from various studies that compared $PM_{2.5}$ exposure of cyclists and drivers. The researchers concluded that the $PM_{2.5}$ exposure of a car driver was only “modestly higher” than that of a cyclist. This study noted that the exposure of some cyclists may be comparable to that of a car driver due to route choice (De Hartog, et al., 2010). Results from studies conducted in the Netherlands may not be transferable to the United States, because bicycle infrastructure is significantly different in the Netherlands than in the United States and the prominence of cycling in the Netherlands greatly reduces the risk of cyclist injury or fatality (OECD, 2013). The lack of transferability demonstrates the need for similar studies in the United States.

A few exposure studies have been conducted in Spain. The Institute of Environmental Assessment and Water Research (Spain) partnered with the National Institute for Public Health and the Environment (Netherlands) to compare air pollutant exposure of different modes of transportation among 20 European cities. This study compiled findings from many different exposure studies conducted using different instruments, techniques, and methodologies and concluded that of the four studied modes of transportation (bicycle, car, bus, and metro), pollutant measurements were highest for the car and the least for the bicycle (Karanasiou, et al., 2014). Due to the many differences between the compiled studies, there were many variables that had to be considered. The variables were divided into four categories: personal factors, mode factors, road traffic factors, and meteorological factors. Some of the most influential characteristics on pollutant exposure included traffic volumes, travel speed, distance between vehicles, and fuel type (Karanasiou, et al., 2014).

Researchers from the Center for Research in Environmental Epidemiology (Spain) completed an air pollutant exposure study for four modes of transportation in Barcelona, Spain. The collected data for walking, cycling, riding a bus, and driving a personal vehicle on two routes was divided into five sampling time periods. Three of the sampling periods were traffic peaks (morning, lunch, evening) and two were non-peaks (midmorning, afternoon). The pairwise analysis showed that overall exposure to all monitored pollutants was greatest for driving a car and the least for walking. This finding lead researchers to conclude that exposure is directly related to proximity to vehicle exhaust. When analyzing the exposure of cyclists, researchers did not consider whether the routes had designated, separated cycling infrastructure (De Nazelle, et al., 2012).

The Imperial College of London has also produced a few pedestrian exposure studies. Kaur, et al. (2005) conducted a pedestrian exposure study in central London. Personal air pollution monitors were used to measure exposure in the morning and the afternoon of volunteers walking along the roadway. As expected, the $PM_{2.5}$ exposure was higher in the morning. It was also found that the recording from the personal monitors were higher than the recordings from fixed location monitors along the roadway. This difference was hypothesized to be from the participants' proximity to roadway traffic (Kaur, et al., 2005).

Another study from the Imperial College of London compared fine particulate matter and carbon monoxide exposure of vehicle drivers, cyclists, and pedestrians using both mobile personal monitoring devices and fixed location monitors. The fixed location monitors were found to be less representative depictions of the air quality in the urban environment, because the fixed monitors were located away from vehicle traffic. Additionally, the study found that car drivers have the highest exposure to fine particulates and carbon monoxide due to the proximity to the emission source (Kaur, et al., 2007).

There have been fewer efforts to understand pollutant exposure and mode choice in the United States. However, researchers from the University of California-Berkeley conducted a scripted exposure study in 2013 that monitored pollutant concentrations on two cycling routes. The first route was a bicycle boulevard with very limited interaction with vehicle traffic and the second route was shared-road, high traffic corridor. The study found that exposure to particulate matter, carbon monoxide, and black carbon was greater for all study participants on the second route (Jarjour, et al., 2013).

These studies showing the pollutant exposure reduction by separating cycling infrastructure by increasing the distance from vehicle traffic also bring up a question at a segment-level of whether pollutant exposure of cyclists would be influenced by the type of cycling infrastructure available (i.e. shared-road vs separated cycle track). Though some studies have experimented with the use of stationary air quality sensors to test the difference in ultra-fine particle concentrations for a conventional bike-lane and a parking protected cycle track, there is still further research needed to understand variations along a route.

Due to increased distances from vehicle traffic, separated cycling infrastructure could have better air quality. Researchers from McGill University completed an air-quality data collection campaign that monitored ultrafine particle and black carbon concentrations along cycling routes in Montreal. The objective of the study was to understand the influence of cycling infrastructure type on cyclists' pollutant exposure. Research assistants cycled pre-defined routes with sensor-equipped bicycles. The routes consisted of diverse cycling infrastructure that represented the many urban microenvironments. In order to understand the relationship between pollutant concentration and cycling facility type, researchers mapped concentrations spatially and developed a regression analysis model. The primary finding from this analysis was that multi-use trails showed the lowest concentrations for both ultrafine particles and black carbon. Additionally, cyclists were exposed to lower pollutant concentrations on local roads. The authors recommend that urban cycling networks consist of local, low-volume roadways (Farrell, et al., 2015).

Researchers from the School of Public and International Affairs at Virginia Tech and the Department of Civil, Environmental, and Geo- Engineering at the University of Minnesota estimate that pollutant concentrations can be reduced by 20% by rerouting cyclists to roadways that are one block or more from major, high-traffic roadways in Minneapolis, Minnesota (Hankey, et al., 2015). These researchers also used facility-demand models and land use regression models to estimate block-level exposure during rush-hour in Minneapolis, Minnesota and identified 20% of local roadways where shifting cyclists from high-traffic roads to adjacent low-traffic roads, pollutant exposure would be reduced by approximately 15% (Hankey, et al., 2016).

Other relevant efforts in the United States have looked to quantify the societal benefits of increased cycling and reduced pollutant emissions. Using the Community Multiscale Air Quality (CMAQ) model, the EPA Benefits Mapping Analysis Program (BenMAP), and the World Health Organization Health Economic Assessment Tool (HEAT), Grabow, et al. (2011) from the University of Wisconsin-Madison estimated that the annual average $PM_{2.5}$ concentration would decrease by 0.1 μg/m3 and the annual health benefits for the region would exceed $4.94 billion if 50% of personal vehicle trips were converted to bicycle trips.

The findings from this literature review demonstrate the need for further exploration of spatial and temporal variation of cyclists' pollutant exposure. Cyclists' pollutant exposure has been the focus of many European studies. Most of the studies found that cyclists' pollutant exposure was less than or equivalent to that of other modes of transportation. However, other studies hypothesize that cyclists may risk greater pollutant exposure, because breathing frequency is much greater when cycling, the number of particulates that remains in the respiratory tract increase while exercising, and cycling trips usually take longer to complete.

Though researchers have found distance from vehicle traffic to be a strong influence on cyclists' exposure, there is still further research needed to understand which specific types of cycling infrastructure are better or worse for cyclists based on exposure to air pollutants. Additionally, there has not been extensive examination of the temporal variation of cyclists' pollutant exposure. Further research needs to be conducted to understand when the healthiest time of day for cycling is based on PM exposure.

2.4 Overview of Low-Cost Air Quality Sensors

Personal Air Pollution Sensors (PAPS) have greatly increased in popularity with recent advances in technology. These advances have drastically reduced the cost of air pollution monitors and have increased the accessibility of air pollutant monitoring technology. Technologies, such as the Plantower™ PMS5003 sensor retail for about $40, whereas commercial-grade equipment costs upwards of $20,000. According to the South Coast Air Quality Management District (SCAQMD)'s intercomparison tests of nineteen low-cost $PM_{2.5}$ sensors made by different companies, the Plantower™ PMS5003 sensor had the highest correlation (R_2>0.93) with the expensive commercial-grade sensors used by the Environmental Protection Agency (SCAQMD, 2017).

Other research has been conducted to determine if low-cost air quality sensors can be used in place of expensive equipment. Environmental scientists from the University of Pisa, Department of Information Engineering conducted a study to determine if wifi and battery-operated sensors could be used to monitor air quality. The researchers created a network of low-cost sensors in Lucia referred to as *uSense*. The sensors were placed in strategic locations with different expected pollutant concentrations. The concentration data collected from *uSense* was not as accurate as the official monitoring system. However, the study concluded that low-cost sensors still serve an important purpose. The benefit of using low-cost monitoring systems is that the sensors are smaller and can be placed in a variety of locations. Many of these locations have not been monitored by the higher-cost, bulky systems. Monitors are also more accessible at a lower price, which encourages people to place monitors in lots of different locations. The vast network of sensors can provide a more comprehensive air quality overview of a region (Brienza, et al., 2015).

The University of California-Berkeley explored the reliability and potential benefits associated with affordable $PM_{2.5}$ sensors. The use of the low-cost sensors has greatly expanded datasets for certain areas, creating a more comprehensive overview of the air pollution epidemiology. When compared to commercially available equipment, an off-the-shelf sensor with readily available hardware performed as well under similar conditions at the same time scale (R_2=0.60). The data from the low-cost and commercially available equipment correlated the strongest over 24-hour time periods (R_2=0.72). Researchers also found that near-roadway monitoring with inexpensive, portable systems is comparable with the concentrations collected at background monitoring sites (Holstius, 2014). These findings demonstrate that commodity hardware can potentially be used as a dependable method for monitoring $PM_{2.5}$.

Though low-cost air quality sensors can greatly increase the quantity of concentration data, performance of these readily available sensors depends on the atmospheric composition and meteorological conditions (Castell, et al., 2017). Researchers from the Norwegian Institute for Air Research (NILU) tested 24 identical sensors and found that the performance of low-cost sensors is variable and that low-cost sensors are not preferable for performing high accuracy data collections. However, the sensors are suitable for determining PM exposure and for raising public awareness of the importance of air quality (Castell, et al., 2017).

The accuracy of the low-cost air quality sensors can be improved by calibrating the sensors prior to monitoring (Holstius, et al., 2014). Research published by *Atmospheric Measurement Techniques* compared concentrations recorded by commercial grade monitoring systems and by low-cost sensors over 1-hour and 24-hour periods. It was determined that there is less variance in the concentrations collected from the two systems over 24-hour periods. In conclusion, low-cost monitors can be used to depict the air quality of a location over an extended period, but readings may be less reliable in smaller time increments (Holstius, et al., 2014).

Other studies have explored the limitations and challenges associated with using low-cost air quality sensors. Researchers from the International Laboratory for Air Quality and Health and Queensland University of Technology found that the performance of low-cost air particle mass sensors was limited in humid or foggy conditions (Jayaratne, et al., 2018). The low-cost sensors tested were Sharp GP2Y, Shinyei PPD42NS, Plantower PMS1003, Innociple PSM305, and the Nova SDS011. None of the tested sensors had a dryer to remove excess atmospheric moisture prior to measurement. Water in the sample resulted in significantly higher concentrations of PM_{10}. Humidity exceeding 75% impacted the PM concentrations of all the tested sensors. Researchers concluded that low-cost PM sensors should not be used to monitor if air quality standards are being met. They recommended that in humid environments, low-cost PM sensors are equipped with a dryer at the inlet to ensure more accurate PM concentrations (Jayaratne, et al., 2018).

A similar conclusion was found by the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA). Atmospheric scientists from ENEA determined that low-cost air quality sensors should not be used to indicate whether an area is meeting air quality standards (Penza, et al., 2014). Low-cost air sensors are best used as personal monitors or as stationary nodes in large monitoring networks. The sensors are too variable and inaccuracies in measurements are triggered by a variety of environmental factors. Because of the inconclusive results from previous studies, additional tests were conducted to determine the feasibility of using low-cost air quality sensors for measuring street-level air quality.

In addition to an overview of low-cost air quality sensors, the literature review summarized three other topics related to the experimental design of the CAR-TEEH studies: (1) adverse health effects from particulate matter (PM) exposure, (2) factors that affect air quality and contribute to varying particulate concentrations, and (3) methodologies for measuring human exposure to PM for different modes of transportation. The findings from the literature review suggest it is necessary to control for certain meteorological factors and roadway characteristics. The literature review also found approaches to measuring PM exposure, which were used as references in developing data analysis parameters and methodologies for these studies.

CHAPTER 3. MONITORING IN-CABIN PARTICULATE MATTER EXPOSURE DURING PARATRANSIT TRANSPORT

3.1 Objectives

Paratransit transport provides transportation options for seniors and individuals that cannot access fixed route bus or rail systems. Unlike fixed route bus or rail systems, paratransit transport has longer ingress and egress times to accommodate passengers with disabilities that may take longer to enter and exit the vehicle. This accommodation leads to longer idling times, often with the doors of the paratransit bus open. Longer idling times can increase air pollutants in the cabin of the vehicle and elevate the particulate matter (PM) exposure of both paratransit passengers and operators. This project seeks to characterize PM exposures for both paratransit passengers and operators. To characterize PM exposures for both paratransit passengers and operators, the research team monitored PM concentrations ($PM_{2.5}$ and PM_{10}) inside the cabin of paratransit buses operating in two locations in the southeast United States during typical daily routes.

3.2 Methodology

This section details impactful characteristics of the two study locations, the instrument and measuring principle used for monitoring, and the set-up of the instrument in the cabin of the paratransit bus.

3.2.1 Study Locations

In-cabin PM concentrations were measured for paratransit operations in Nashville, Tennessee and Atlanta, Georgia (Figure 1). The two cities are in the southeast region of the United States and have large paratransit bus fleets. The measurements in Nashville were conducted on gasoline-powered paratransit buses operated by *WeGo Public Transit*, the local paratransit operator while those in Atlanta were conducted on both gasoline and diesel-powered buses operated by the *Metropolitan Atlanta Rapid Transit Authority (MARTA) Mobility.*

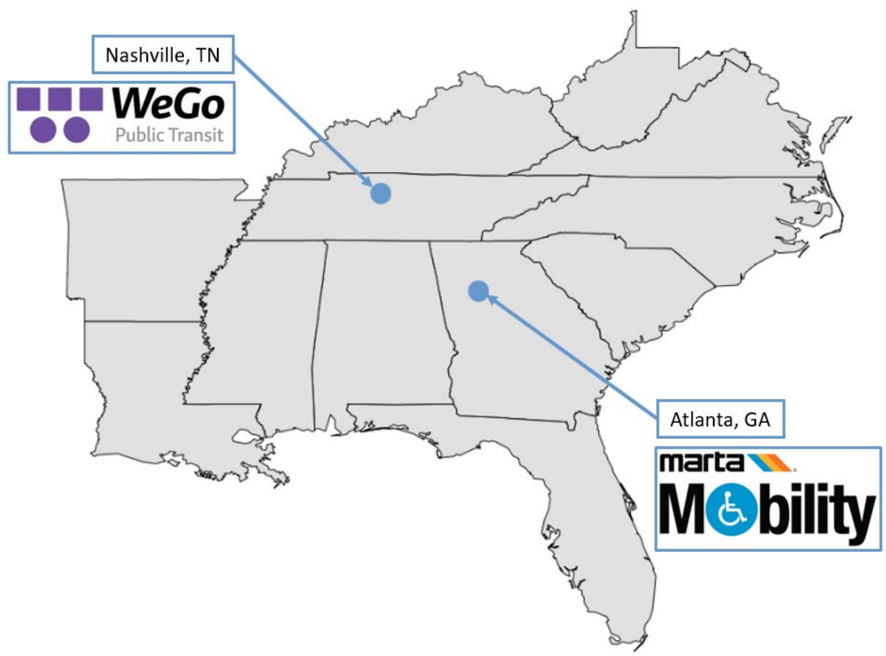

Figure 1 - Map of study locations.

PM concentrations inside the cabin of the paratransit buses were collected for two days in each city. For these measurements, the research team used the GRIMM® 1.109 aerosol spectrometer equipped with a radially symmetric iso-kinetic sampling head near the breathing height of the passenger(s).

3.2.1.1 *WeGo Public Transit* Overview

WeGo Public Transit provides ADA-designated service within Davidson County and the City of Nashville, Tennessee. These areas are serviced by 91 lift vans fuelled by gasoline (CDM Smith, 2018).

Origin-destination data were used to identify the most requested locations for paratransit pick-up and drop-off in May 2018. The twenty most requested locations by *WeGo Public Transit* riders are shown in Figure 2. Most of the stops were concentrated in the city limits of Nashville with other stops scattered at the major hospitals throughout Davidson County.

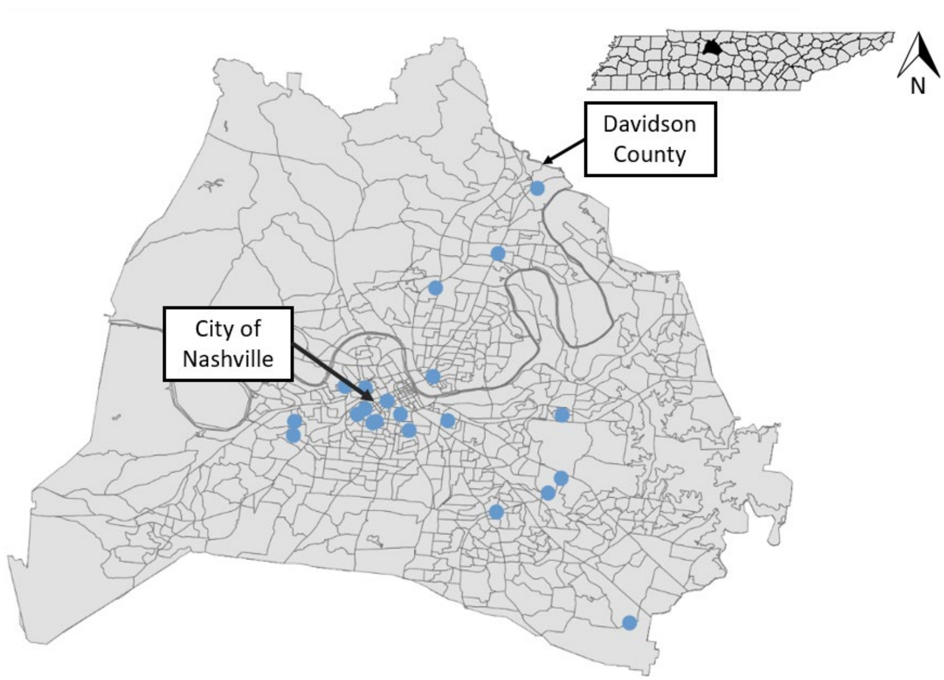

Figure 2 - *WeGo Public Transit* most requested pick-up and drop-off locations in May 2018.

3.2.1.2 *MARTA Mobility* Overview

MARTA Mobility provides ADA-designated service in Fulton, DeKalb, and Clayton Counties as well as within the City of Atlanta. These areas are serviced by 173 lift vans fueled by either gasoline or diesel.

Origin-destination data were used to identify the most requested locations for paratransit pick-up and drop-off in May 2018. The twenty most requested locations by *MARTA Mobility* riders are shown in Figure 3. Most of the stops were concentrated in the city limits of Atlanta. The stop markers are scaled to the frequency that stop was requested.

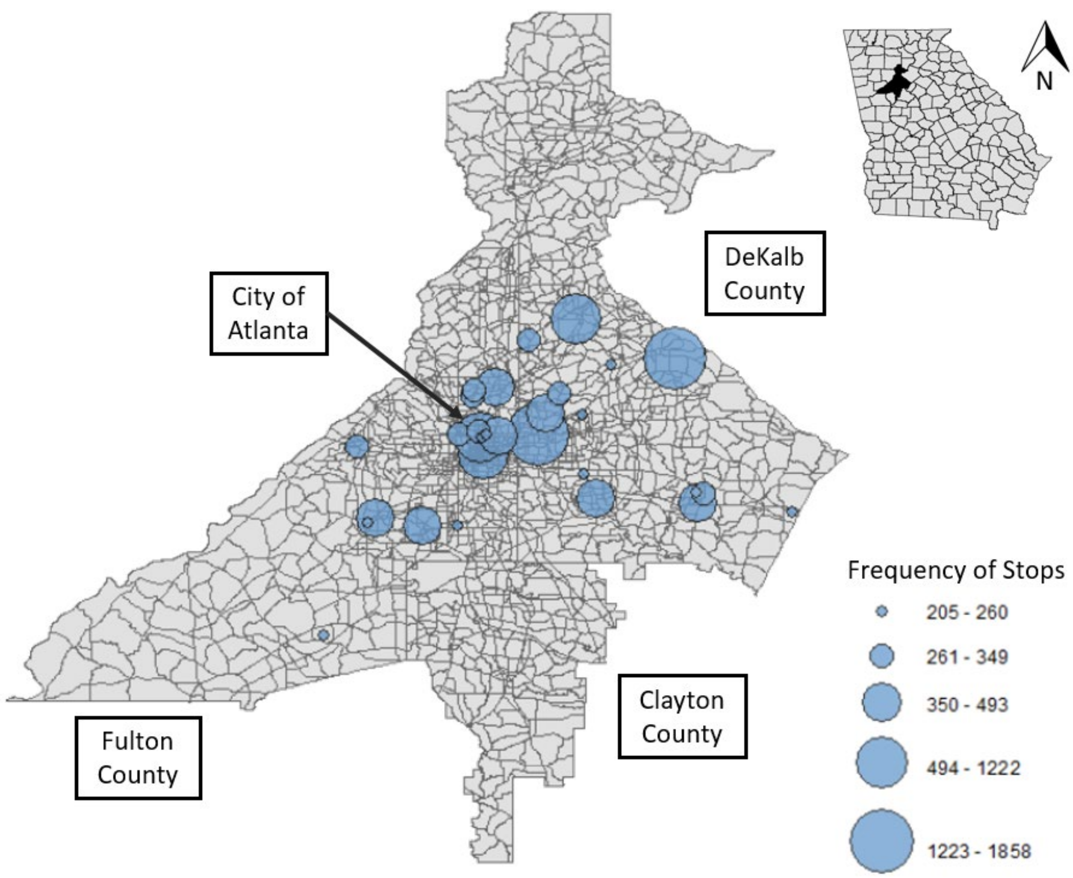

Figure 3 - *MARTA Mobility* most requested pick-up and drop-off locations in May 2018.

3.2.1.3 Frequently Requested Stops

To gauge the representativeness of the sampling days in terms of route length and travel times, the research team used origin-destination data (one month from each city) to identify the most likely pick-up and drop-off locations. Over 80% of the stops by *WeGo Public Transit* were at a hospital, care facility, or dialysis center. Medical facilities were also amongst the most popular *MARTA Mobility* stops. Over 60% of the stops by *MARTA Mobility* were at a hospital, care facility, or dialysis center. Figure 4 shows the distribution of requested stop destinations for each operator.

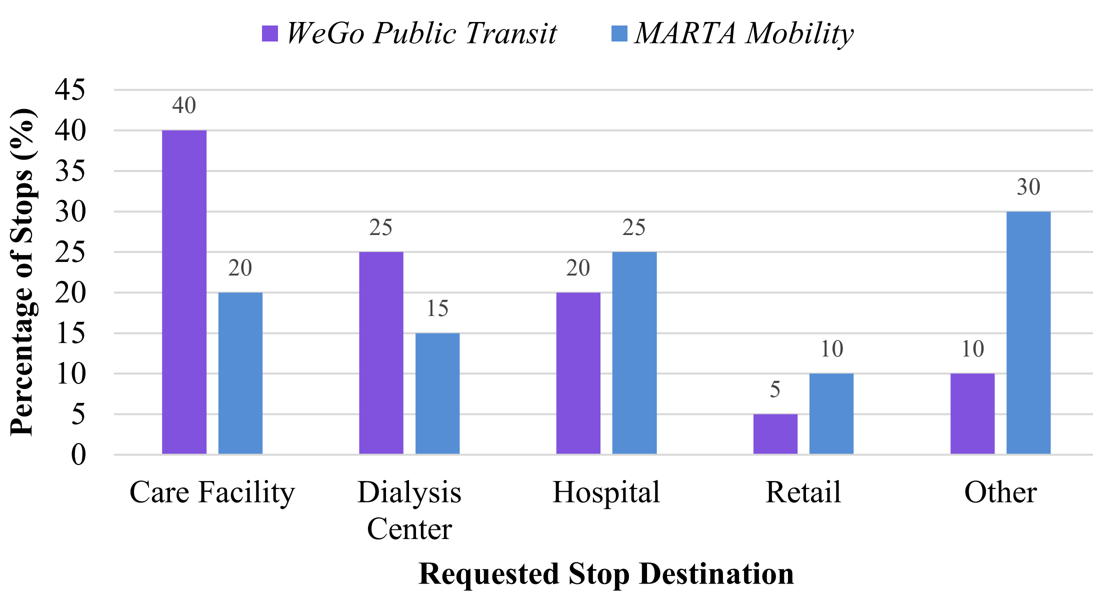

Figure 4 - Distribution of requested stop destinations in May 2018.

3.2.1.4 Pre-Existing Conditions of Ridership

In addition to the origin-destination data, data for pre-existing health conditions of paratransit riders were analyzed. The data were provided by *WeGo Public Transit*. Though *MARTA* did not provide information about pre-existing conditions, comparable percentages of pre-existing conditions can be expected for *MARTA Mobility* riders. Approximately 19% of ridership that reported a pre-existing health condition had a cardiovascular or respiratory disease. Cardiovascular and respiratory diseases make individuals more sensitive to PM. The duration of a passenger's PM exposure is estimated to be between 30 minutes to an hour while completing a trip using paratransit services.

3.2.2 Instrumentation

The field measurements for $PM_{2.5}$ and PM_{10} concentrations during transport were recorded using a GRIMM® 1.109 aerosol spectrometer equipped with a radially symmetric isokinetic sampling head. The GRIMM® 1.109 (Figure 5) is a portable laser aerosol spectrometer that is classified as an EPA equivalent method for both $PM_{2.5}$ and PM_{10} (there is no federal reference method for PM_1).

Figure 5 - GRIMM® 1.109 aerosol spectrometer (Technik GmbH & Company, n.d.).

The GRIMM® 1.109 intakes air using an internal volume flow-controlled pump. The system scatters light from a single particle with a semiconductor laser as shown in Figure 6. The particles are counted by light pulses and sorted by reduction in light intensity. The counts are then output in six second intervals (Technik GmbH & Company, n.d.).

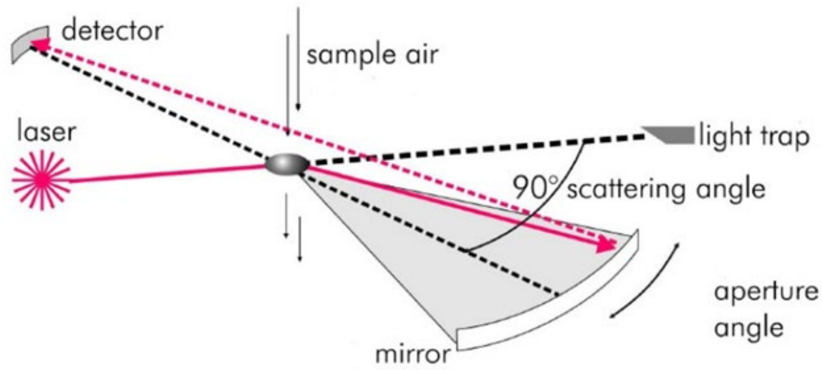

Figure 6 - Measuring principle of GRIMM® 1.109 aerosol spectrometer (Technik GmbH & Company, n.d.).

An internal algorithm converts size-resolved particle counts to an equivalent mass concentration ($\mu g/m^3$). The model also differentiates between sizes of particles (PM_{10}, $PM_{2.5}$, PM_1) and occupational health measures (respirable, thoracic, alveoli) (Technik GmbH & Company, n.d.).

3.2.3 Data Collection

The project team placed the GRIMM® 1.109 aerosol spectrometer with its sampling head inside the cabin of the paratransit bus. The GRIMM® 1.109 aerosol spectrometer was strapped to a safety cushion behind the driver's seat. The experiment setup is shown in Figure 7. The setup was similar on both *WeGo Public Transit* and *MARTA Mobility* buses. The *WeGo Public Transit* paratransit buses have a fare box behind the driver's seat whereas the *MARTA Mobility* buses have additional passenger seating. The monitoring device was placed at approximately the breathing level of an individual seated on the bus. The research team placed the spectrometer on the paratransit bus prior to departure from the terminal and retrieved the device after the bus completed its daily route and returned to the terminal.

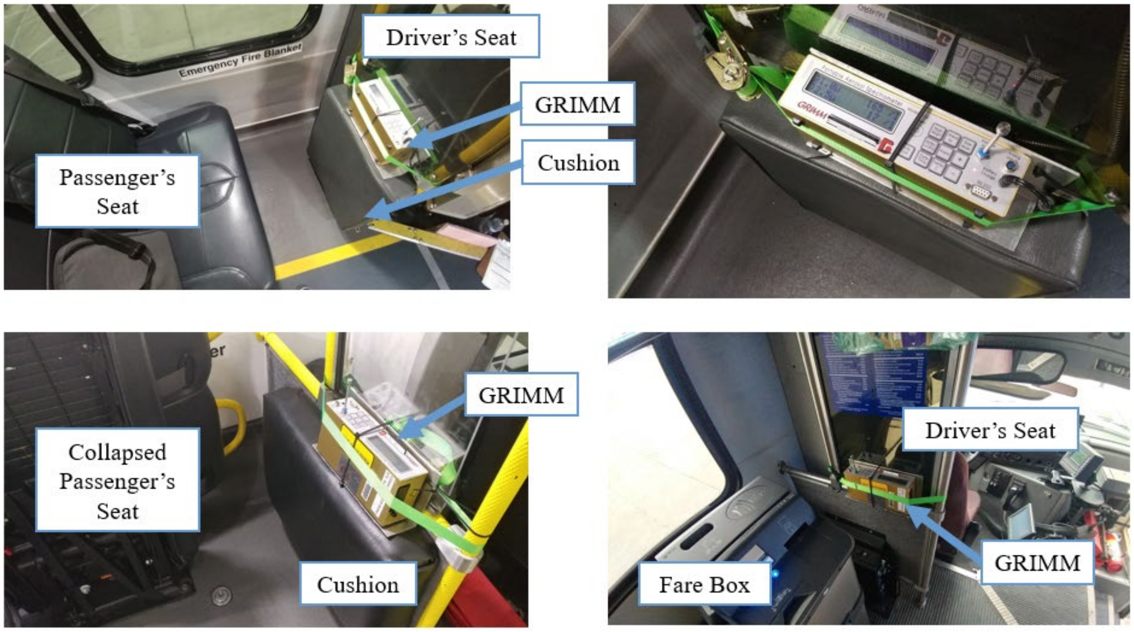

Figure 7 - Experiment set-up in the cabin of the paratransit bus.

3.3 Results

This section details the results of monitoring the in-cabin $PM_{2.5}$ and PM_{10} concentrations of the paratransit bus. Included are time series from monitoring of *WeGo Public Transit* and of *MARTA Mobility*, comparison of the measurements, and comparison of measurements to urban background air quality.

3.3.1 WeGo Public Transit (Nashville) PM Measurements

In-cabin PM concentrations were recorded in Nashville on December 4, 2018 and December 5, 2018. The observed $PM_{2.5}$ and PM_{10} concentrations inside the cabin of the paratransit buses during the buses' daily routes are shown in Figure 8 through Figure 13. On these time series, the scheduled stop times are labeled according to the schedule of services for the respective days. The schedule was provided by *WeGo Public Transit*.

In-cabin PM concentrations increased when the bus stopped and opened its doors to board passengers. During transport on the first day of monitoring (Figure 8 and Figure 9), there was a significant increase in PM concentration when the doors opened for an extended period. The hypothesis for the increased in-cabin PM measurements is that the paratransit buses have long stops that allow time for passengers to enter and exit the bus. During passenger ingress and egress, the bus remains idling with the doors open. This idling may have contributed to the increased PM concentrations.

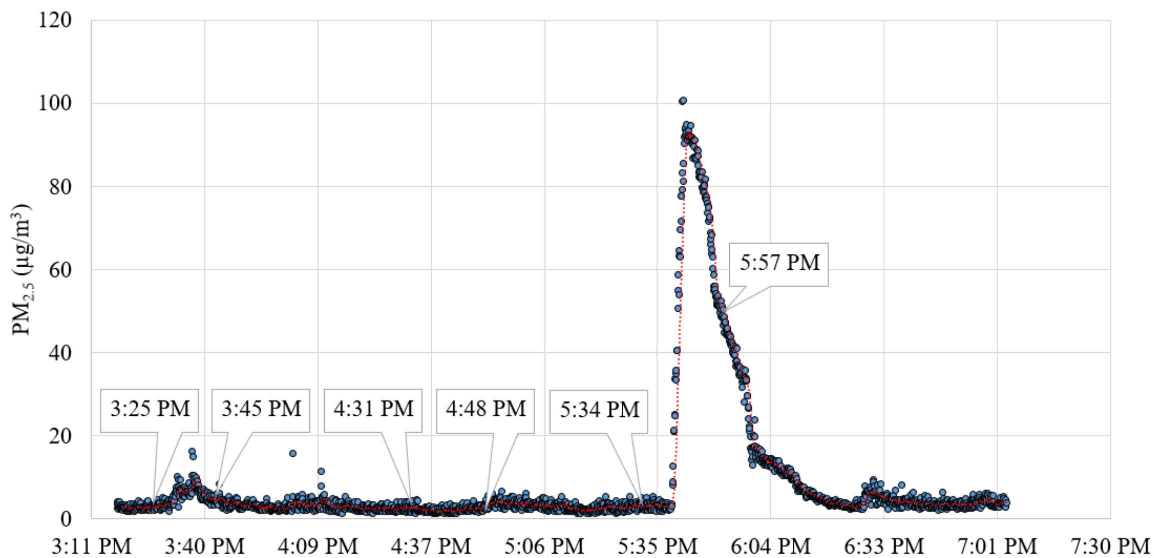

Figure 8 - *WeGo Public Transit* in-cabin $PM_{2.5}$ concentrations recorded on December 4, 2018.

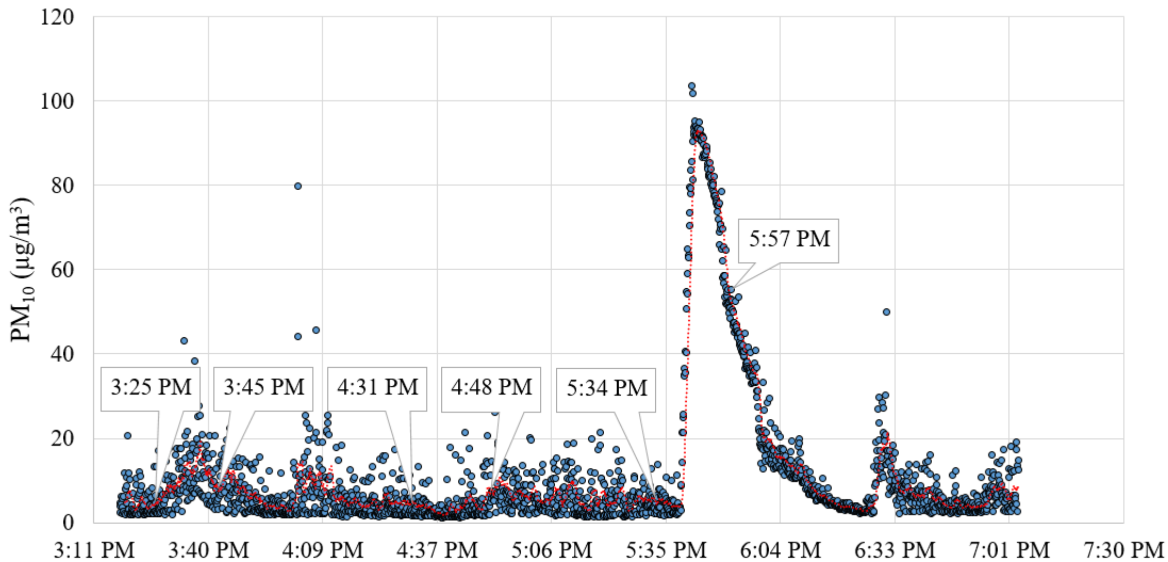

Figure 9 - *WeGo Public Transit* in-cabin PM_{10} concentrations recorded on December 4, 2018.

PM concentrations are greatly impacted by meteorological conditions. Temperatures during the monitoring days ranged from 30 to 40 degrees Fahrenheit and the humidity varied throughout the day from 50 to 76 percent. There was no precipitation on December 4, 2018, however, before measurements on December 5, the second day of monitoring (Figure 10 and Figure 11), there was a light snowy precipitation before the start of measurements and a thin layer of snow on the ground during the start of data collection. The cooler temperatures and snowfall may have resulted in the significantly lower PM concentrations than those recorded on the previous day. Snow may have also caused lower traffic volumes and therefore a lower mass flux from the roadway. PM concentrations observed in the evening, after the temperature rose and the snow stopped, (Figure 12 and Figure 13) were more comparable to those observed on the first day of monitoring.

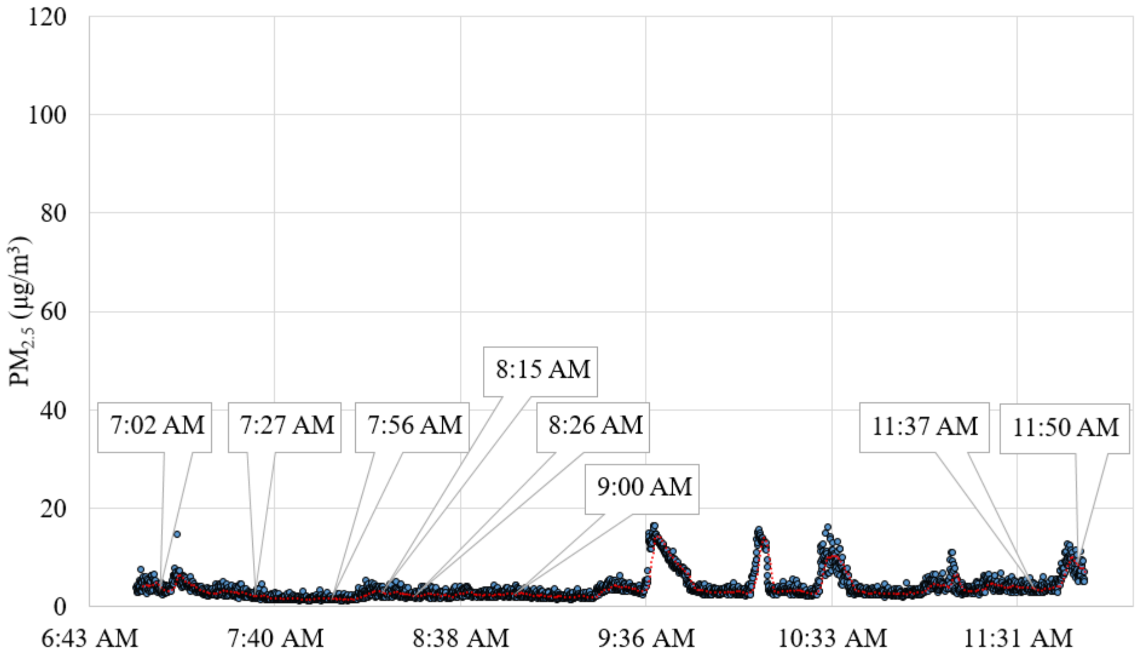

Figure 10 - *WeGo Public Transit* in-cabin $PM_{2.5}$ concentrations recorded the morning of December 5, 2018.

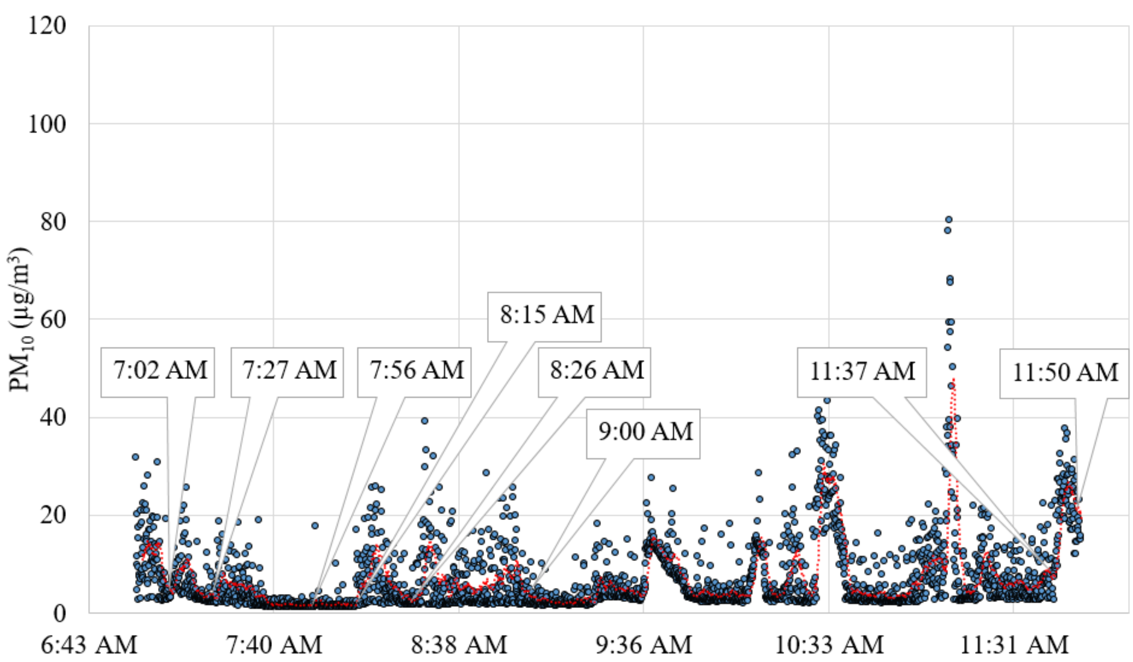

Figure 11 - *WeGo Public Transit* in-cabin $PM_{2.5}$ concentrations recorded the morning of December 5, 2018.

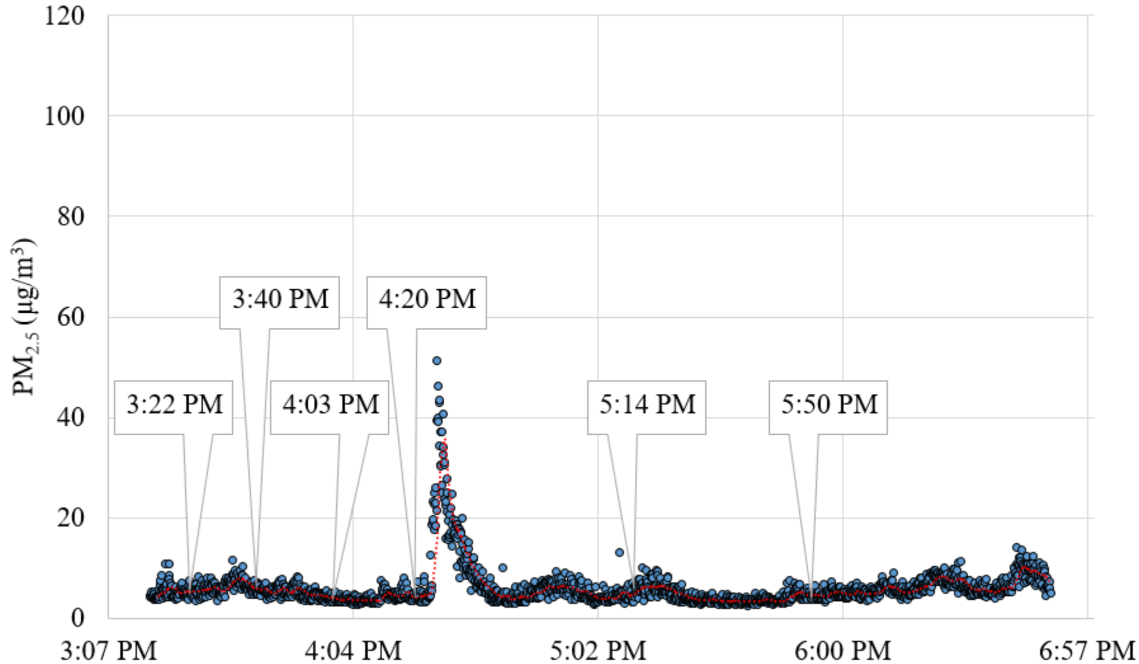

Figure 12 - *WeGo* Public Transit in-cabin $PM_{2.5}$ concentrations recorded the evening of December 5, 2018.

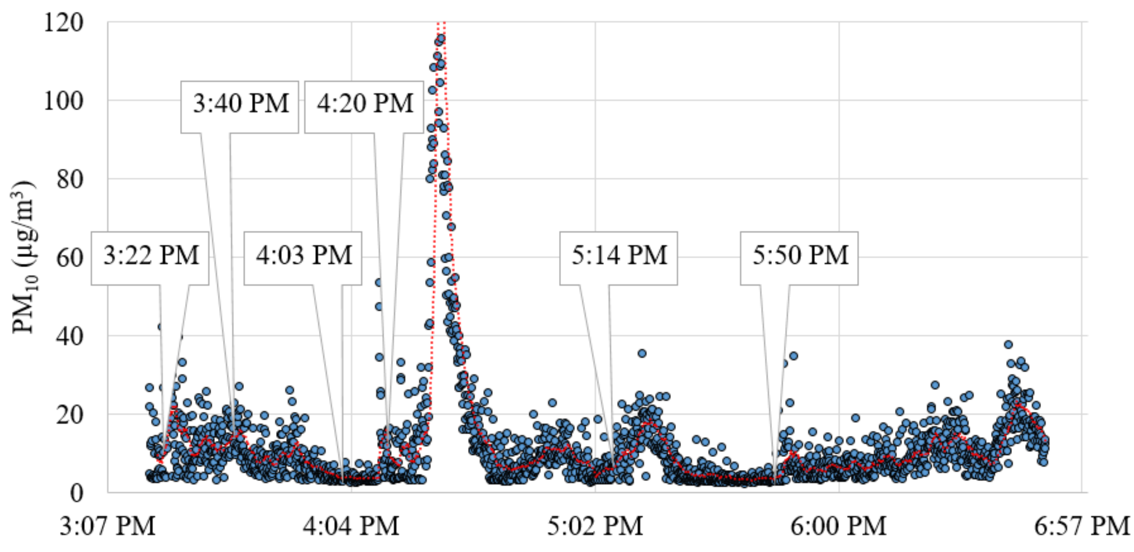

Figure 13 - *WeGo* Public Transit in-cabin PM_{10} concentrations recorded the evening of December 5, 2018.

The red boxes shown on the insets (upper right) of Figures 14 and Figure 15 indicate when during monitoring an increase in $PM_{2.5}$ concentration occurred. Figure 14 highlights an increase in $PM_{2.5}$ concentration during the first day of monitoring. It took approximately thirty minutes for the $PM_{2.5}$ concentration to return to the baseline exposure. This pattern of gradual particle dispersion is also shown in Figure 15. Figure 15 shows an increase in $PM_{2.5}$ concentration during the second day of monitoring.

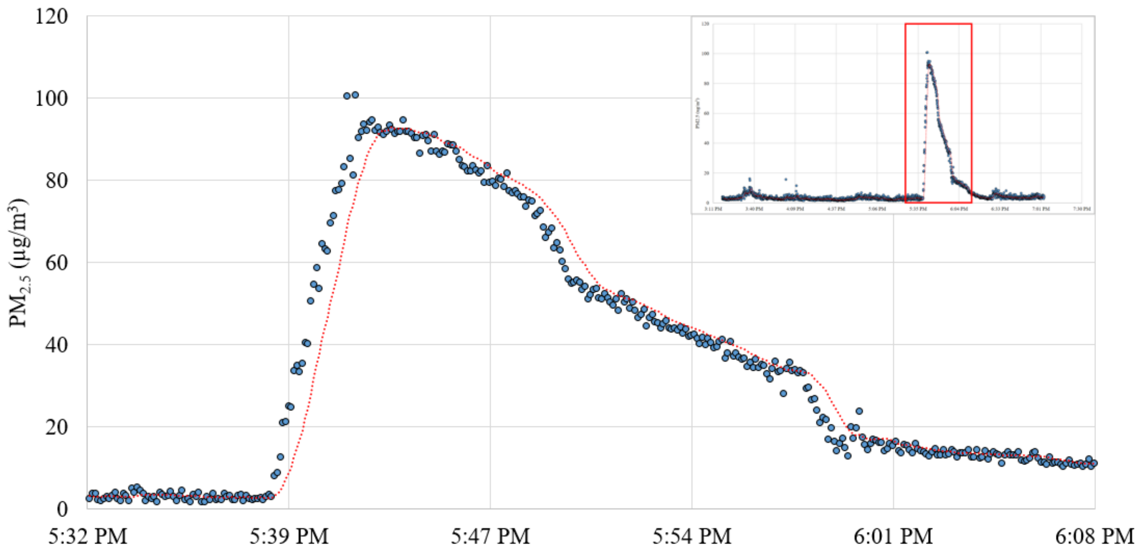

Figure 14 - *WeGo Public Transit* in-cabin $PM_{2.5}$ concentrations recorded December 4, 2018.

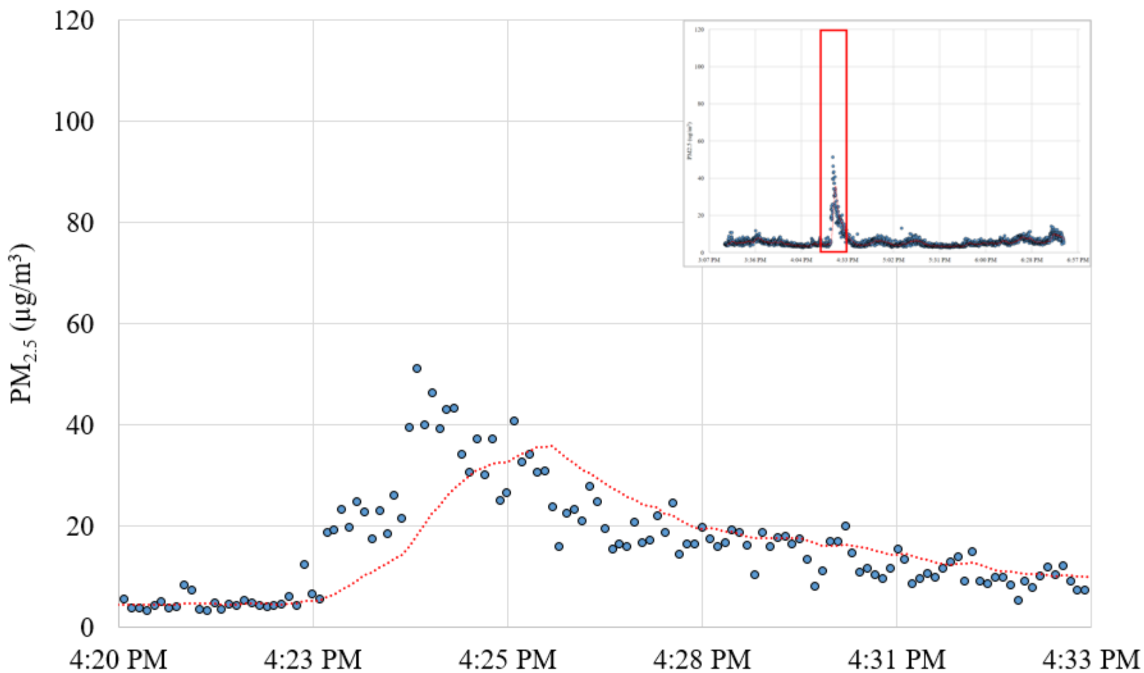

Figure 15 - *WeGo Public Transit* in-cabin PM$_{2.5}$ concentrations recorded the evening of December 5, 2018.

3.3.2 MARTA Mobility (Atlanta) PM Measurements

The same procedure was used to collect data on *MARTA Mobility* buses. The in-cabin PM concentrations were recorded in Atlanta on October 25, 2018 and October 30, 2018. Temperatures during the monitoring days ranged from 50 to 60 degrees Fahrenheit. There was no precipitation during monitoring and the humidity varied throughout the day from 50 to 70 percent.

The stop times were not provided by *MARTA Mobility*. However, there were increases in PM concentrations during transport similar to the increases observed on the *WeGo Public Transit* buses. On October 25, the PM concentrations were recorded on a gasoline-powered bus and the measurements on October 30 were recorded on a diesel-powered bus. These measurements show the differences between PM exposure from riding a gasoline bus and a diesel bus.

The $PM_{2.5}$ and PM_{10} concentrations inside the cabin of the gasoline-powered bus are shown in Figure 16 and Figure 17, respectively.

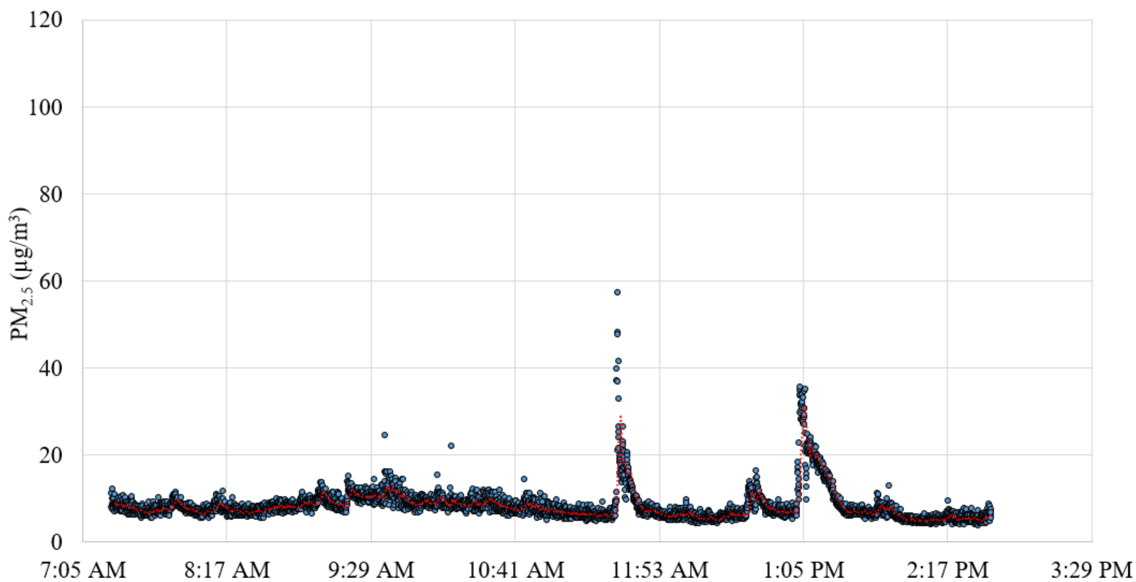

Figure 16 - *MARTA Mobility* in-cabin $PM_{2.5}$ concentrations recorded October 25, 2018 in gasoline-powered bus.

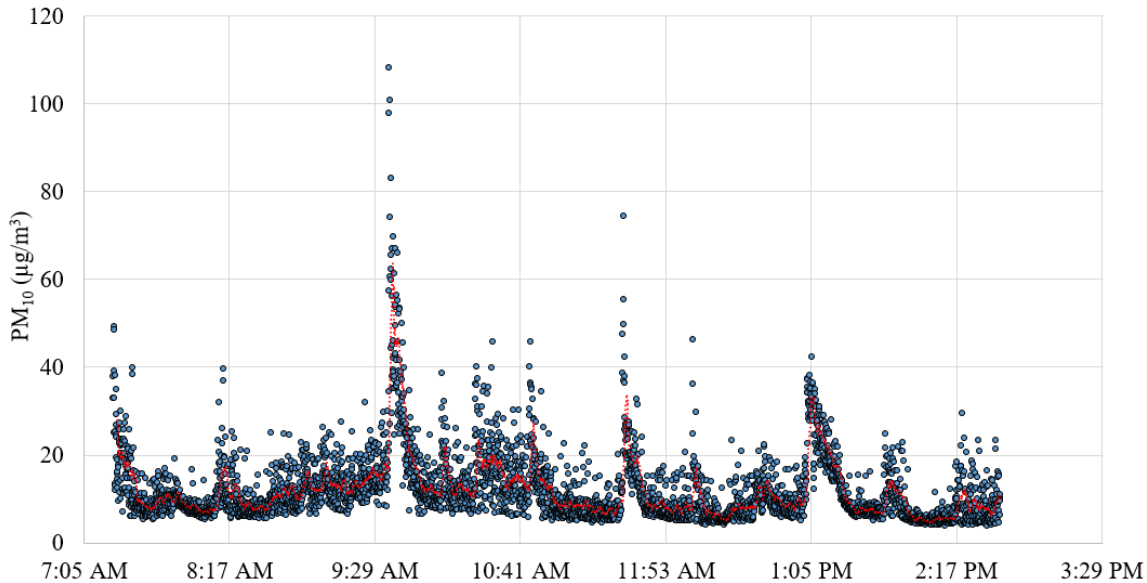

Figure 17 - *MARTA Mobility* in-cabin PM_{10} concentrations recorded October 25, 2018 in gasoline-powered bus.

There were a few increases in $PM_{2.5}$ concentrations followed by the gradual dispersion of particles. The gradual return to the baseline $PM_{2.5}$ concentration took approximately ten minutes. Figure 18 highlights an increase in $PM_{2.5}$ concentrations observed on the gasoline-powered bus.

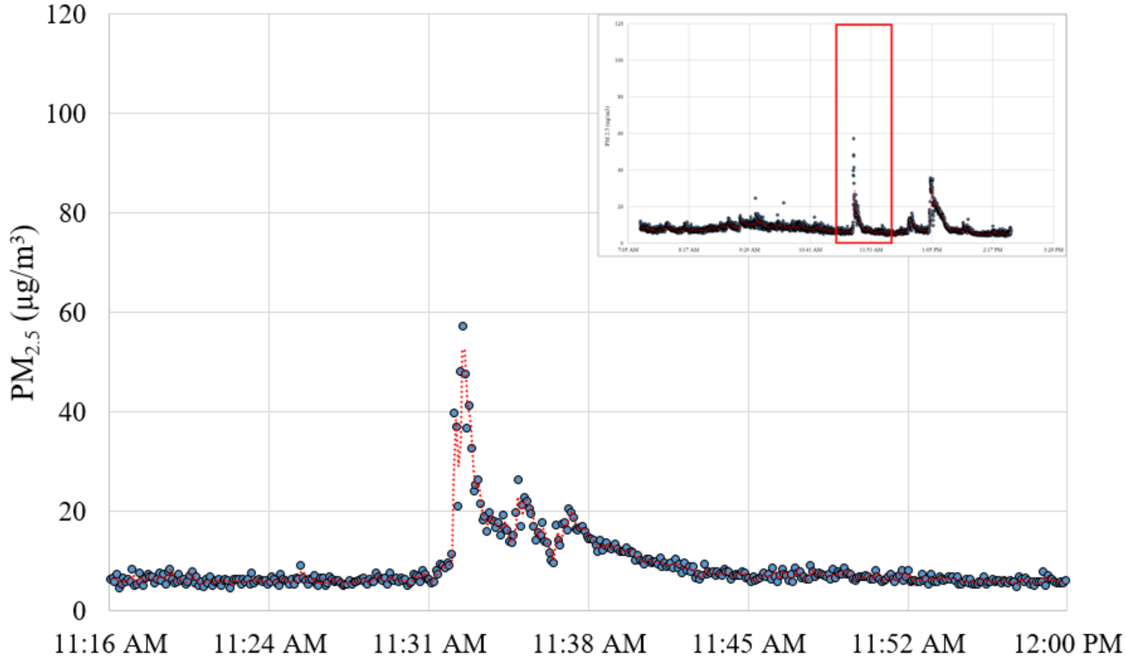

Figure 18 - *MARTA Mobility* in-cabin $PM_{2.5}$ concentrations recorded October 25, 2018 in gasoline-powered bus.

The $PM_{2.5}$ and PM_{10} concentrations inside the cabin of the diesel-powered bus are shown in Figure 19 and Figure 20, respectively. The time series for both days of monitoring display somewhat similar patterns between the in-cabin concentrations of the gasoline and diesel-powered buses.

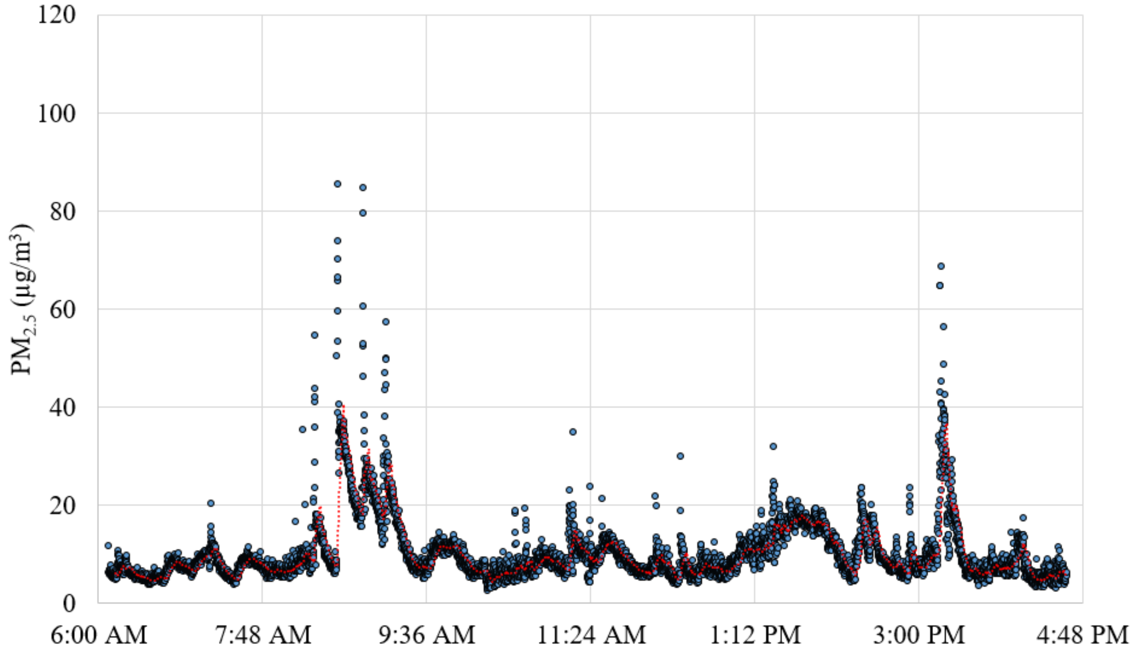

Figure 19 - *MARTA Mobility* in-cabin PM$_{2.5}$ concentrations recorded October 30, 2018 in diesel-powered bus.

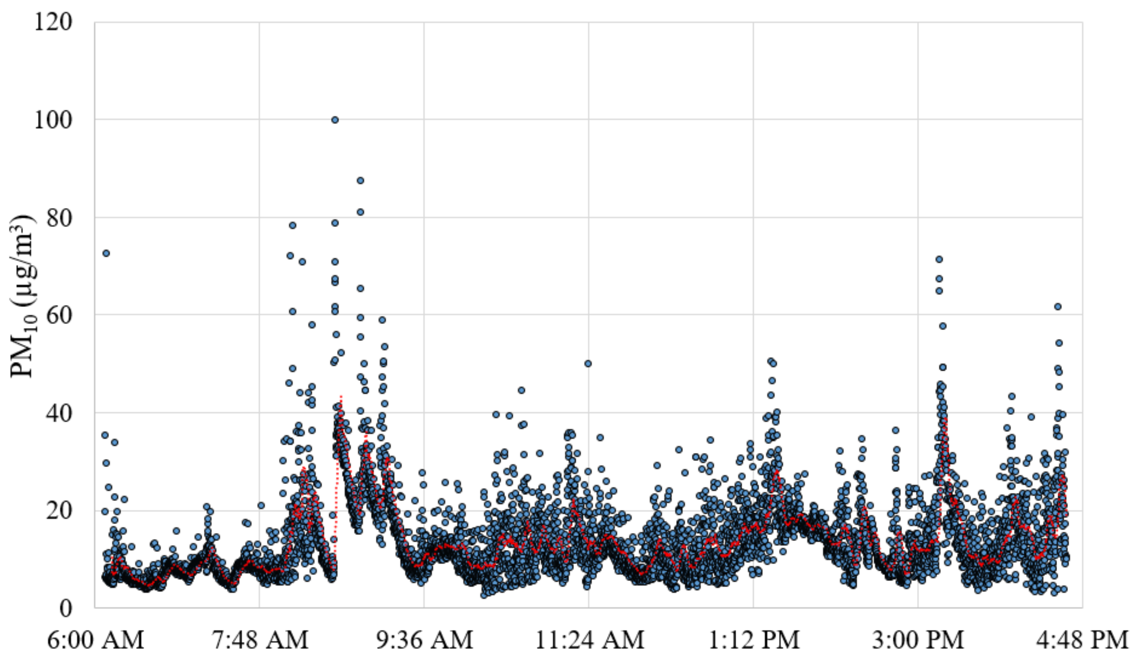

Figure 20 - *MARTA Mobility* in-cabin PM$_{10}$ concentrations recorded October 30, 2018 in diesel-powered bus.

There were several increases in $PM_{2.5}$ concentration. After the initial spike in $PM_{2.5}$, the concentrations immediately began to decrease and eventually returned followed to the baseline $PM_{2.5}$ concentration. It took approximately fifty minutes after one of the observed increases for the $PM_{2.5}$ concentration to stabilize.

Elevated $PM_{2.5}$ exposure was longer in the diesel-powered bus than in the gasoline-powered bus. However, the longer exposure could have also occurred due to multiple subsequent stops on the diesel-powered bus. The duration between stops was not long enough to allow the $PM_{2.5}$ concentration to stabilize.

Figure 21 shows increases in $PM_{2.5}$ concentrations observed on the diesel-powered bus in greater detail. Though stop times were not available for *MARTA Mobility*, the hypothesis is that there were subsequent stops that caused the $PM_{2.5}$ concentration to increase when the bus doors opened repeatedly. Whenever the bus door opened, pollutants from the idling bus and the surrounding area entered the cabin of the paratransit bus. The cabin of the paratransit bus flooded with pollutants until the doors were closed for an extended time and the particles dispersed allowing PM concentrations to stabilize.

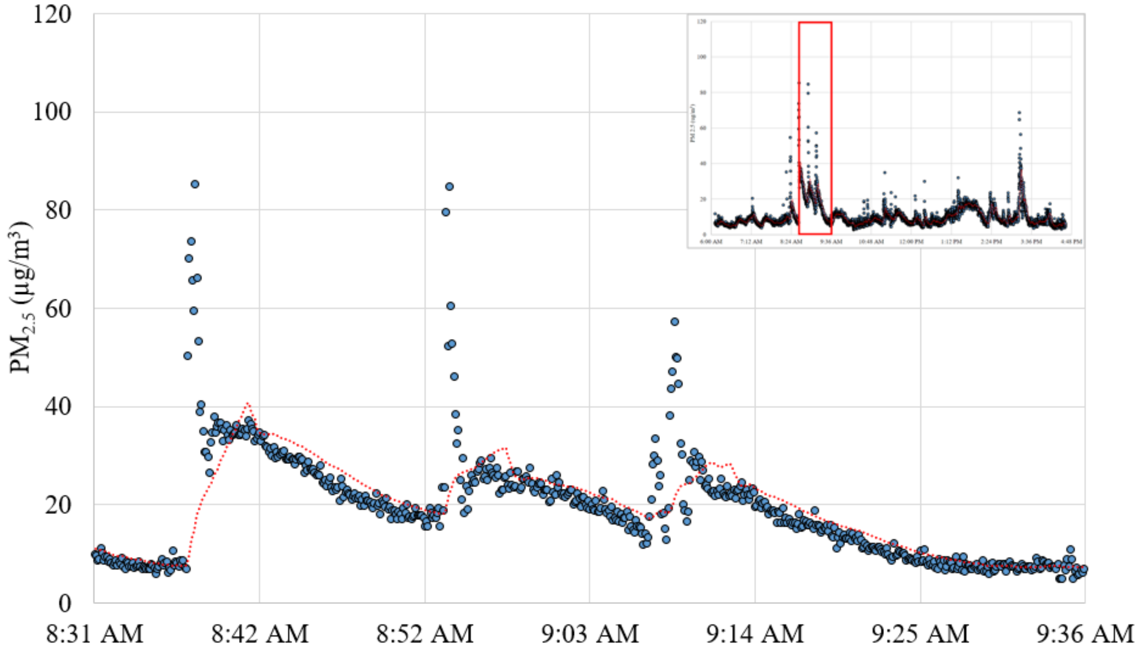

Figure 21 - *MARTA Mobility* in-cabin $PM_{2.5}$ concentrations recorded October 30, 2018 in diesel-powered bus.

3.3.3 Comparison of PM Measurements on WeGo Public Transit (Nashville) & MARTA Mobility (Atlanta)

WeGo Public Transit and *MARTA Mobility* operate similarly. Both paratransit operators offer door-to-door services. Their daily routes are variable, because they are determined by riders' requests. However, there are many commonalities between the most requested stops. The paratransit buses in both cities frequently transport people to hospitals, care facilities, and dialysis centers. Riders are exposed to PM emitted by the vehicle as well as PM from sources surrounding the stops.

Researchers found that the $PM_{2.5}$ and PM_{10} concentrations increase when the bus opens its doors to pick-up or drop-off passengers. The $PM_{2.5}$ and PM_{10} concentrations in Nashville and Atlanta were similar with baseline concentrations of approximately 10 $\mu g/m^3$.

3.3.4 Comparison of In-cabin PM Measurements to Urban Background Concentration

Recorded PM concentrations are a combination of local and background pollutant sources. In order to understand the pollutant contribution from local sources, a "background correction" was used. The background correction or the subtraction of the background concentration from the observed pollutant concentration is a common approach to rescale the observed concentrations to reflect the emissions from street level processes (Lenschow, et al., 2001) (De Nazelle, et al., 2012).

A background correction was used to understand how the $PM_{2.5}$ concentrations inside the *MARTA Mobility* buses compared to the $PM_{2.5}$ concentrations recorded at the Georgia Ambient Air Monitoring Program's site. The monitoring site is located at the Georgia Department of Transportation's Transportation Management Center and records the $PM_{2.5}$ concentration every hour. This concentration is regarded as the PM concentration of Atlanta, Georgia.

Figure 22 and Figure 23 show the observed $PM_{2.5}$ concentrations corrected for background concentration inside the MARTA Mobility buses on October 25, 2018 and October 30, 2018, respectively. As shown in both Figure 22 and Figure 23, the air quality inside the bus was better than the air quality of the surrounding area in the morning. As monitoring progressed, the air quality became worse than the air quality of the surrounding area and passengers were exposed to $PM_{2.5}$ concentrations that greatly exceeded the background concentration.

The corrected concentrations on the diesel-powered bus at times exceeded 70 $\mu g/m^3$ whereas the corrected concentrations on the gasoline-powered bus did not exceed 50 $\mu g/m^3$

with most of the corrected concentrations ranging from –10 μg/m^3 to 10 μg/m^3. On the respective monitoring days, the gasoline-powered bus was found to have $PM_{2.5}$ concentrations more comparable to the urban background concentration. In comparison, the $PM_{2.5}$ concentrations recorded on the diesel-powered bus tended to exceed the urban background concentration.

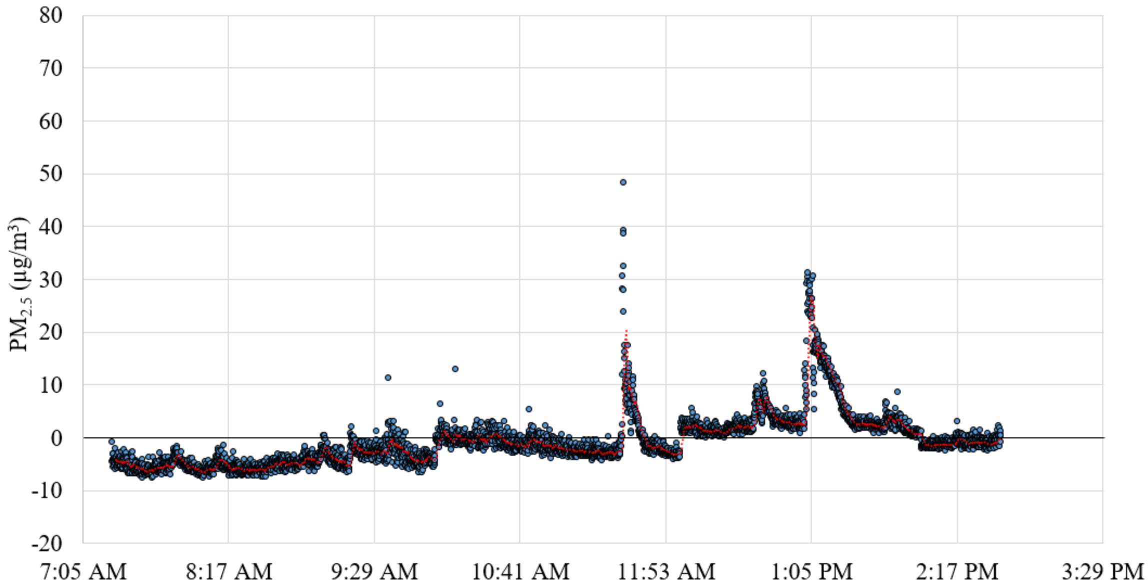

Figure 22 - *MARTA Mobility* in-cabin $PM_{2.5}$ concentrations corrected for background concentration recorded October 25, 2018 in gasoline-powered bus.

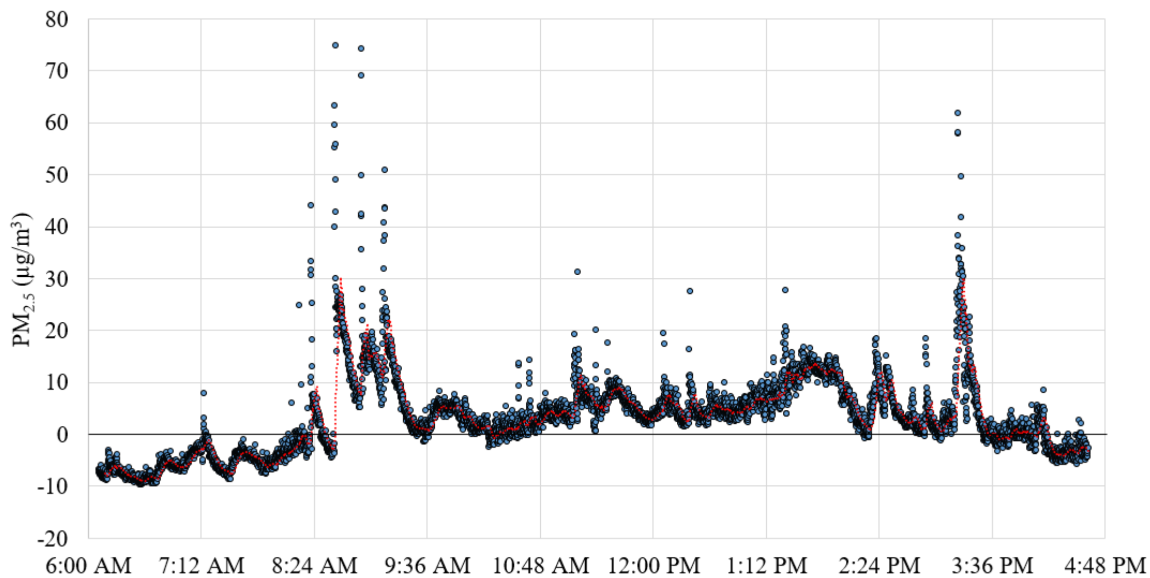

Figure 23 - *MARTA Mobility* in-cabin PM$_{2.5}$ concentrations corrected for background concentration recorded October 30, 2018 in diesel-powered bus.

3.4 Discussion of Results

This experiment was an initial study to access the feasibility of using a dust aerosol spectrometer to monitor PM exposure. The PM measurements recorded on *WeGo Public Transit* (Nashville, TN) and *MARTA Mobility* (Atlanta, GA) demonstrated some patterns of PM exposure associated with paratransit transport. The two primary findings from this study were that (1) PM concentrations increased when the doors of the paratransit bus were open as shown by the increases in PM concentrations corresponding to stop times and (2) that elevated PM concentrations can extend beyond when the doors are closed. After the doors of the bus closed, it took substantial time (between 10 to 30 minutes) for the particles to disperse and the background concentration to stabilize.

This study demonstrated that it is feasible to use a dust aerosol spectrometer to monitor PM exposure of paratransit passengers and operators. However, some limitations should be noted. First, researchers were not permitted to monitor the location or speed/acceleration of the paratransit buses due to privacy concerns from the transit agencies. The stop times and locations were analyzed from schedules provided by *WeGo Public Transit*. GPS and accelerometer data would have allowed researchers to better correlate an increase in PM concentration to a stop. Additional characteristics, such as the use HVAC systems in the buses and whether the HVAC systems were set to recirculate air or use fresh outside air would provide better depictions of the overall experience on the paratransit buses.

Second, without GPS data, researchers could not conclude whether the increases in the in-cabin PM concentrations were from self-pollution from the idling paratransit bus or from local sources at the stop. Roadside bus stops can experience up to 40% higher PM concentrations than the urban background due to motor vehicle exhaust and other local sources (Lenschow, et al., 2001). In order to understand the contribution of other motor vehicles and local sources on the PM exposure of paratransit riders, future studies should measure the PM concentrations inside and outside of the paratransit bus. The use of the background correction attempted to characterize PM exposure of passengers on the paratransit bus in comparison to typical urban background exposure, however the background concentration was not always measured in the vicinity of the route. Further studies should be conducted to understand the health implications of PM exposure on paratransit riders. As the population ages, these studies are essential to provide safe and effective paratransit services.

CHAPTER 4. MEASURING PARTICULATE MATTER EXPOSURE OF URBAN CYCLISTS USING AN INSTRUMENTED BICYCLE

4.1 Objectives

As the popularity of cycling increases, it is transportation planners and engineers who will be responsible for making informed decisions about the types of cycling infrastructure to implement. There has been limited research conducted to understand which types of cycling infrastructure may be better or worse for cyclists' health based on exposure to air pollutants. For example, there has been little research conducted to understand if the air quality of a shared lane is different from that of a separated bike lane. Separated bicycle infrastructure is defined as designated infrastructure (i.e. road striping, paths only for bicycles, etc.) having perpendicular distance from vehicular traffic. Due to further distances from vehicular traffic, it is possible that separated cycling infrastructure could have better air quality. It is also important to recognize that air quality is not only impacted by proximity to vehicular traffic, but also by other factors including meteorology and land use. This study seeks to better understand local cyclists' $PM_{2.5}$ exposure.

The objective of this study is to assess the feasibility of using an instrumented bicycle equipped with low-cost air quality sensors to monitor the $PM_{2.5}$ exposure of cyclists in Atlanta, Georgia. The specific activities to achieve this objective include collecting air quality data for routes composed of different types of cycling infrastructure and mapping the $PM_{2.5}$ exposure of the different routes. The maps will be used to compare types of cycling infrastructure based on the observed $PM_{2.5}$ concentrations.

4.2 Methodology

This section details the sensor selection, sensor calibration, route selection, data collection, and data analysis processes of this study.

4.2.1 Sensor Selection

Cyclists' $PM_{2.5}$ exposure was monitored using an instrumented bicycle (Figure 24). The components of the instrumented bicycle were designed to easily attach to participants' bikes, to need minimal intervention from the research team once attached, and to have minimal impact on cyclists' experiences while collecting PM concentrations and time-dependent spatial data.

Figure 24 - Instrumented bicycle with identified front and rear components.

There are two primary components of the instrumented bicycle: a front and a rear component. The front component is mounted to the handlebar and contains the primary compute functions along with sensors that monitor location, altitude, and ambient environmental conditions. The rear component is attached to the seat-post mounted rack. The rear component houses the proximity sensor, air quality sensors, and power source. Across the two components, the sensor platform integrates readings from twenty different sensors that measure acceleration, directness of path, roadway slope, pavement condition, object proximity, environmental conditions, and air quality. This study only focused on the data collected by the air quality sensors.

This study monitored $PM_{2.5}$ concentrations to assess the feasibility of using low-cost air quality sensors. $PM_{2.5}$, though largely emitted by secondary sources compared to other primary pollutants, is the focus of this study, because it can be monitored by low cost sensors (U.S. Environmental Protection Agency, 2019). Low cost sensors for many of the primary pollutants are far worse in performance (Brienza, et al., 2015) (Holstius, 2014).

$PM_{2.5}$ concentrations were collected using two Plantower™ PMS5003 sensors (Figure 25). Plantower™ PMS5003 sensors use laser scattering to radiate suspending particles in the air, then collect scattering light to obtain the curve of light change with time. The sensors contain microprocessors that calculate equivalent particle diameter and the number of particles with different diameters per unit volume. The Technical Index in the PMS5003 series data manual reports that the PMS5003 sensor has a single response time of one second and a total response time of less than 10 seconds (Plantower, 2016). The response time is the time required for the sensor output to change from its previous state to a final settled value (National Instruments, 2019).

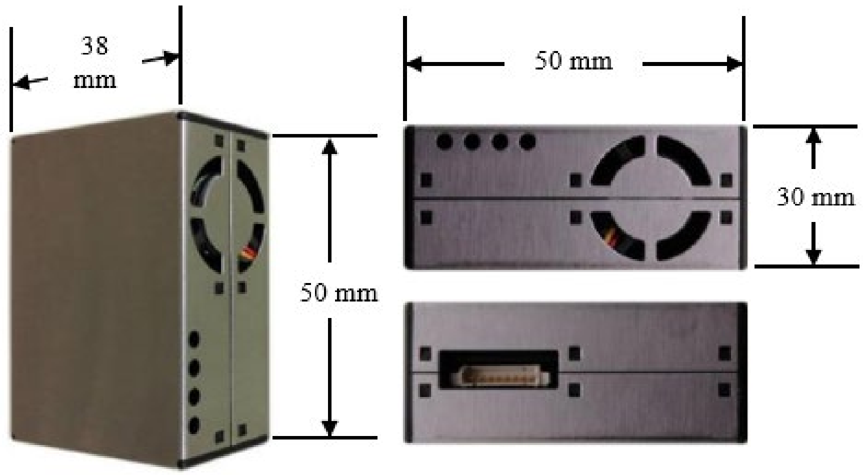

Figure 25 – Plantower™ PMS5003 Digital universal particle concentration sensor (Plantower, 2016).

The sensors are controlled by a Raspberry Pi™ in the rear component and are connected to an Arduino™ Uno in the front component of the instrumented bicycle. The Arduino™ Uno integrates the time-dependent GPS data with the Plantower™ PMS5003 sensor data and stores the integrated data. The recorded $PM_{2.5}$ concentrations with corresponding GPS coordinates and time stamps are output every second.

4.2.2 Sensor Calibration

Personal Air Pollution Sensors (PAPS) have greatly increased in popularity with recent advances in technology. These advances have drastically reduced the cost of air pollution monitors and have increased the accessibility of air pollutant monitoring technology. Technologies, such as the Plantower™ PMS5003 sensor retail for about $40, whereas commercial-grade equipment costs upwards of $20,000.

The PMS5003 sensors were selected for their low cost and small size. The low cost and small size facilitated the data collection process, because the sensors could easily be attached to the bicycle without the threat of harming an expensive piece of laboratory equipment. Additionally, according to the South Coast Air Quality Management District's intercomparison tests of nineteen low-cost $PM_{2.5}$ sensors, the Plantower™ PMS5003 sensor had the highest correlation with the expensive commercial-grade sensors used by the Environmental Protection Agency (SCAQMD, 2017).

To verify the correlation between the measurements of the Plantower™ PMS5003 sensors and the commercial-grade sensor, researchers compared the responses of the GRIMM® 1.109 aerosol spectrometer and eight PMS5003 sensors housed in PurpleAir® systems. The configuration of the GRIMM® 1.109 aerosol spectrometer and PurpleAir® systems is shown in Figure 26.

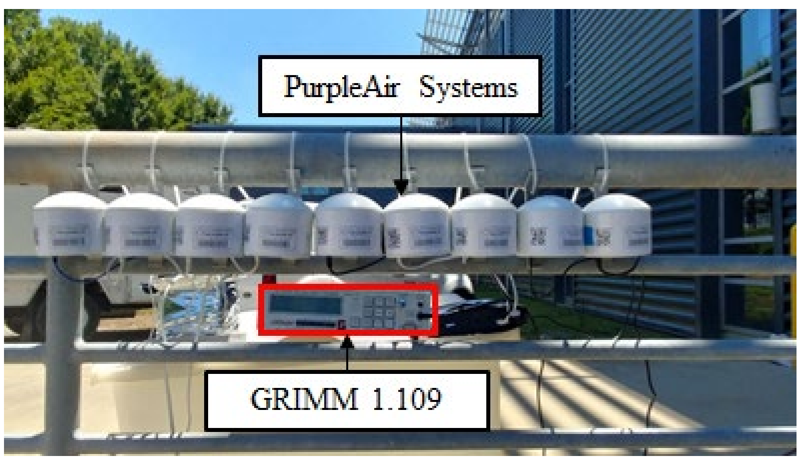

Figure 26 – Experiment set-up for comparison of GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors.

During the comparison, the sensors were tested against both ambient conditions and transient exposure to a known PM source. A challenge sample (i.e. exhaust of an internal combustion engine) was added to the surrounding airspace to test the sensors' responses to transient exposure. The $PM_{2.5}$ concentrations recorded by the GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors during monitoring are shown in Figure 27.

Both instruments produced similar trends, but the instruments differed in magnitude of readings and quickness of response. The GRIMM® 1.109 aerosol spectrometer had a much sharper response to the challenge sample than the PMS5003 sensors did. $PM_{2.5}$ readings were consistently lower by the GRIMM® 1.109 aerosol spectrometer than any by the Plantower™ PMS5003 sensors housed in the PurpleAir® systems.

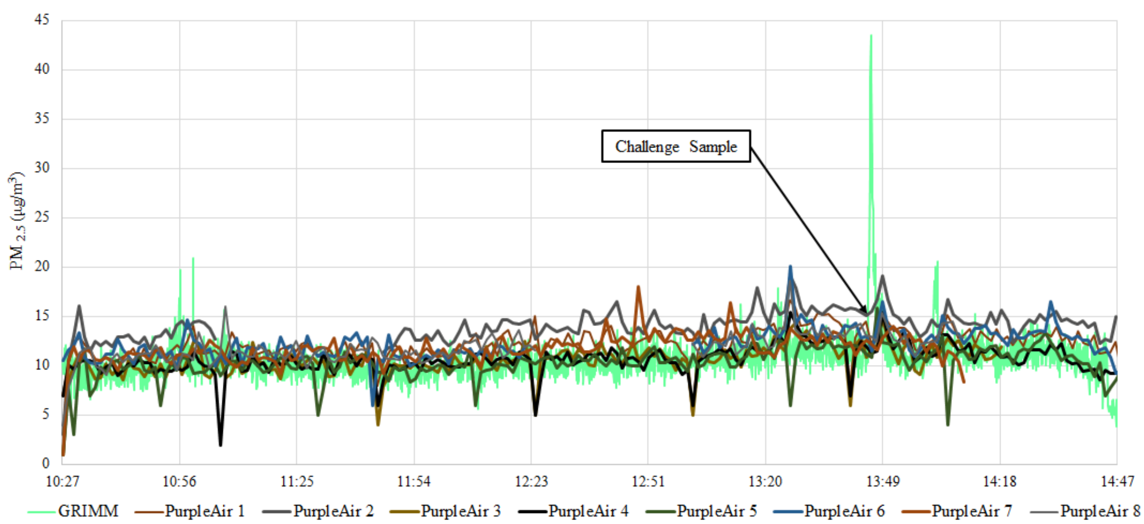

Figure 27 – Time series of $PM_{2.5}$ concentrations recorded by GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors.

In addition to a stationary comparison test, researchers also conducted mobile comparison tests between the PMS5003 sensors and the GRIMM® 1.109 aerosol spectrometer. Thirty-eight runs were conducted with both the GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors attached to the bicycle. The average difference between the $PM_{2.5}$ measurements of the sensors was 0.086 $\mu g/m^3$ with a standard deviation of 7.384 μg/m^3. Overall, the results of the mobile comparison test showed that the $PM_{2.5}$ concentrations recorded by the GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors agreed for most distances on the test runs, with some short distances of large variation, shown in Figure 28.

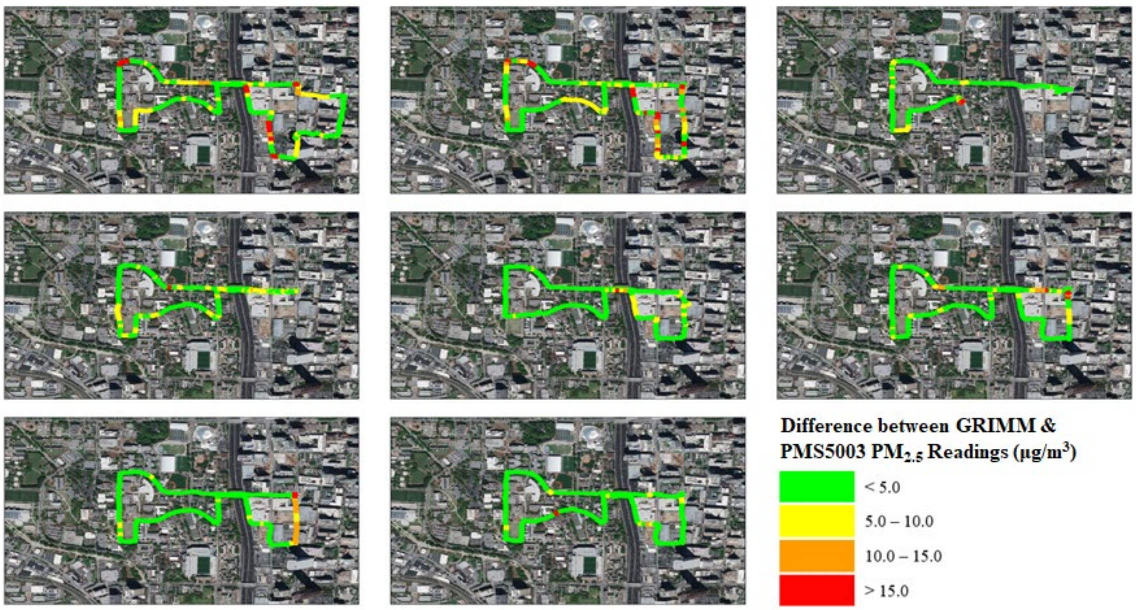

Figure 28 – Difference between GRIMM® 1.109 aerosol spectrometer and PMS5003 sensors during mobile monitoring.

When reviewing the data, researchers found that the route segments with large measurement variation were associated with spikes in the GRIMM® 1.109 aerosol spectrometer $PM_{2.5}$ measurements. The spikes in PM readings from the GRIMM® 1.109 aerosol spectrometer were likely caused by pollutant sources that passed very quickly, such as a heavy-duty truck or bus. Though the magnitudes of the spikes in $PM_{2.5}$ measurements from the GRIMM® 1.109 aerosol spectrometer were much larger than those from the PMS5003 sensors, the PMS5003 sensors still detected an increase in $PM_{2.5}$ and therefore the PMS5003 sensors were concluded to be representative of patterns observed during mobile air quality monitoring.

4.2.3 Route Selection

The research team developed four routes (Figure 29) composed of different types of cycling infrastructure available in Atlanta, Georgia. The routes are in different parts of the city to examine the variation of cyclists' $PM_{2.5}$ exposure within a large urban environment.

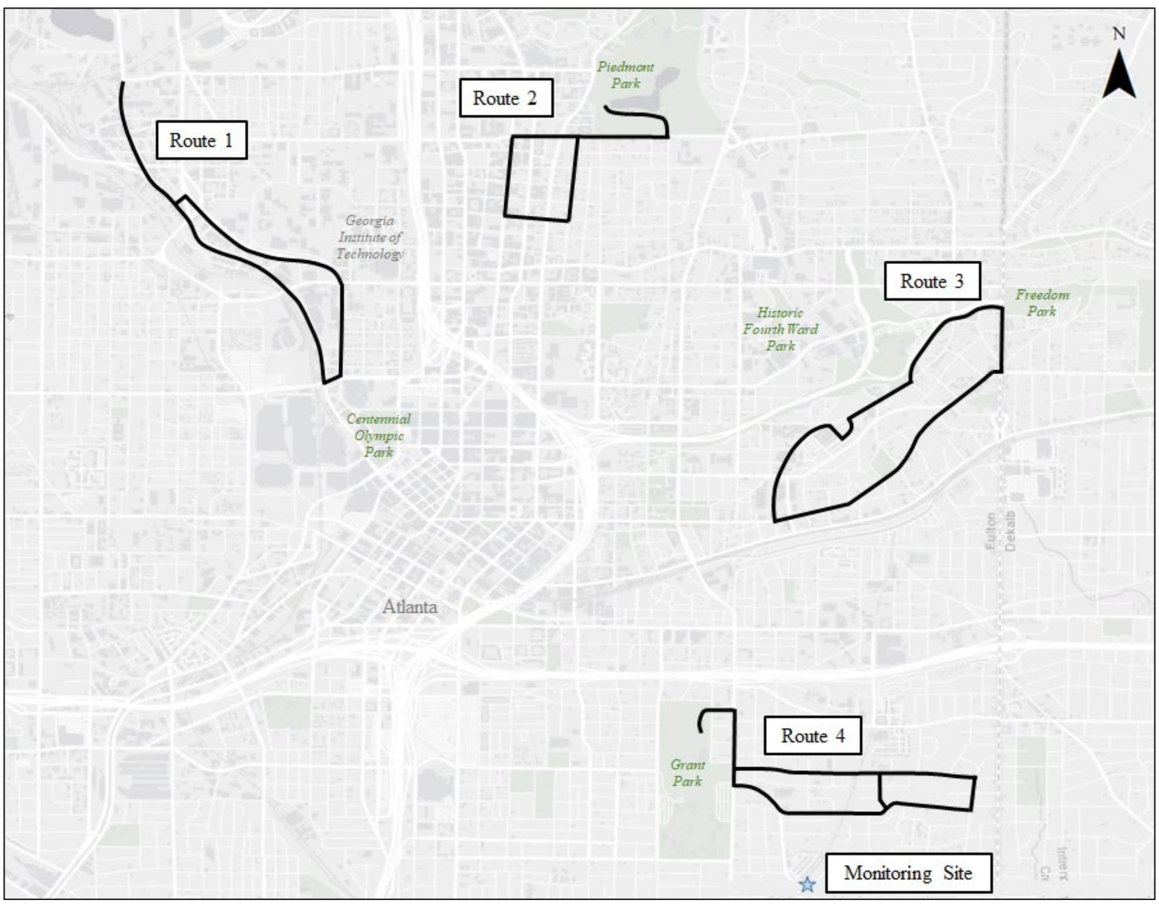

Figure 29 - Overview of routes with monitoring site shown.

To create the routes, researchers first looked at where people are cycling in Atlanta, Georgia. Atlanta has three data sources for cyclists' activity: Ride Report®, Relay Bikeshare®, and Strava®. The data sources represent travel patterns of bike commuters, recreational riders, and sport cyclists, respectively. By combining Ride Report® data from 2018, Relay Bikeshare® data from 2018, and Strava® data from 2014, the research team identified areas with the highest volumes of cyclists and selected those areas as the basis for the four routes. The routes were also designed to be approximately the same distance and to take approximately 30 minutes for cyclists to complete.

In conjunction with the data sources, researchers used a map of Atlanta's cycling infrastructure to develop the routes. The routes were designed to have different types of cycling infrastructure. Each route has segments of low-stress (i.e. parks, shared use trail), medium-stress, and high-stress (i.e. mixed traffic with high vehicular traffic volumes) cycling infrastructure shown in Figure 30 through Figure 33. More detailed descriptions of the route segments are shown in Section 4.3 Results.

Figure 30 - Overview of Route 1 with typical street view of each segment shown.

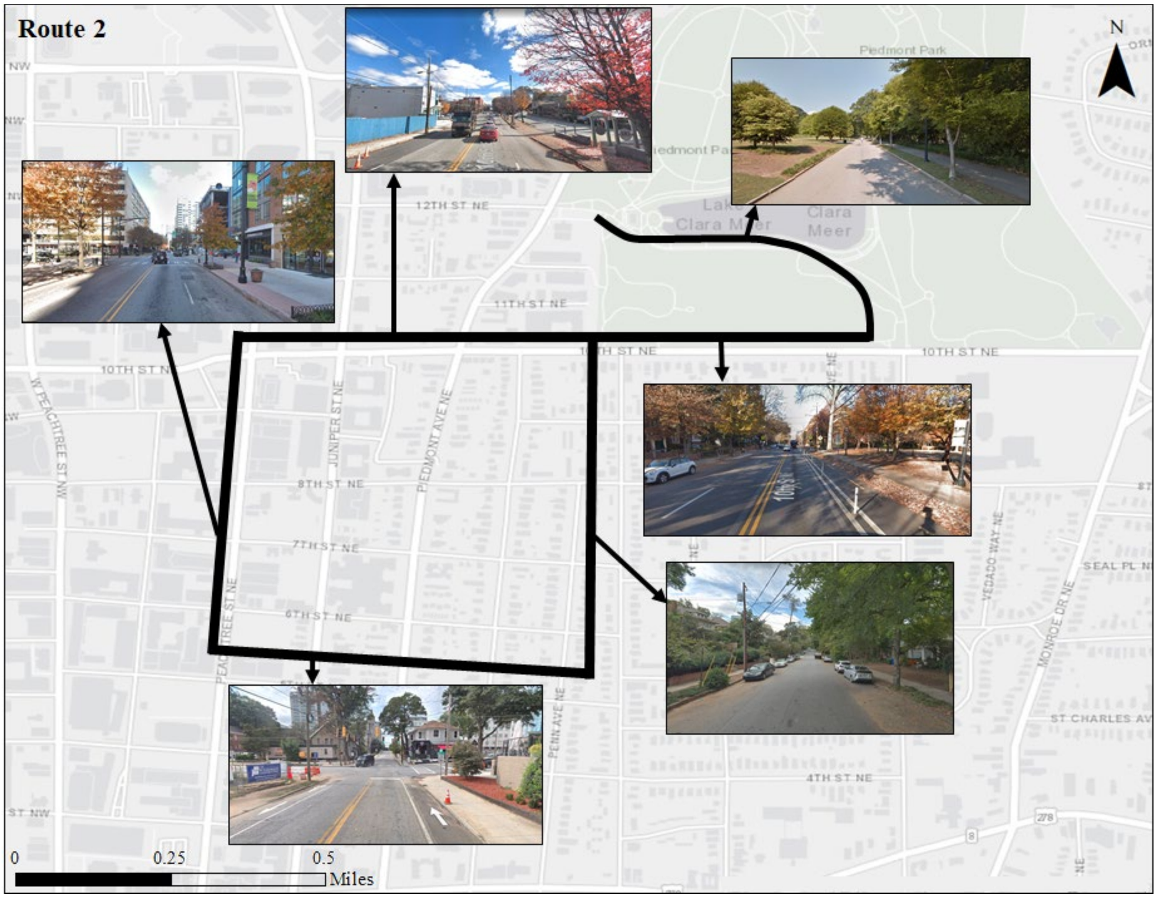

Figure 31 - Overview of Route 2 with typical street view of each segment shown.

Figure 32 - Overview of Route 3 with typical street view of each segment shown.

Figure 33 - Overview of Route 4 with typical street view of each segment shown.

4.2.4 Data Collection

This air quality study is a part of a larger study that seeks to identify factors that impact cyclists' stress using the data recorded by the other sensors on the instrumented bicycle. Therefore, the routes needed to be ridden by cyclists of different comfort levels to observe the differences in behaviors. The four routes were selected to be convenient for many different cyclists in the city and to attract cyclists of all comfort levels.

Study participants elected to ride the instrumented bicycle on one of the four pre-determined routes. During the data collection period, each of the routes was completed by at least five participants. The rides were completed at different times throughout the day to explore how PM concentrations vary in relation to time of day. The time of monitoring and meteorological conditions of each run are summarized in Table 1.

Table 1 - Overview of runs and meteorological conditions during runs.

Date	Start Time	Background $PM_{2.5}$ (μg/m^3)	T (°F)	WS (mph)	WD	RH (%)
Route 1						
12/05/18	10:00	7.7	43	13	NW	49
01/26/19	15:00	3.9	46	5	NNW	50
01/31/19	14:30	4.1	50	0	CALM	32
02/24/19	10:15	6.6	63	21	WNW	38
04/11/19	11:45	6.6	76	16	SSE	52
Route 2						
11/09/18	16:15	6.3	52	16	NW	86
11/16/18	10:45	6.2	56	8	NW	45
11/20/18	16:45	9.3	33	23	NW	56
12/03/18	17:25	7.2	51	10	NW	54
12/04/18	16:50	6.7	40	10	NW	58
01/09/19	17:30	4.4	51	17	W	32
02/09/19	17:00	2.2	52	13	E	30
04/02/19	9:00	7.3	46	12	ENE	46
04/02/19	12:00	6.0	54	7	ENE	37
04/02/19	15:00	12.0	62	13	N	31
04/02/19	17:00	7.5	63	12	NW	31
04/02/19	19:00	11.2	61	13	NW	13
Route 3						
12/03/18	15:00	7.8	55	10	NW	47
12/05/18	16:30	5.2	34	9	N	56
02/04/19	18:20	9.2	58	3	SW	78
02/09/19	16:00	4.3	48	10	E	41
04/16/19	11:00	5.3	62	8	SE	37
Route 4						
02/13/19	15:00	0.7	49	8	WNW	41
04/03/19	13:00	5.1	67	3	SSW	24
04/15/19	16:00	5.6	64	13	WNW	32
04/15/19	17:30	5.8	65	18	NNW	32
04/22/19	17:00	8.1	81	5	W	25

4.2.5 *Data Processing*

Data processing steps included correcting for background $PM_{2.5}$ concentration, segmenting the routes, and assigning cycling infrastructure types, roadway functional classifications, and land use types to the route segments.

4.2.5.1 Background Concentration

Recorded PM concentrations are a combination of local and background pollutant sources. In order to understand the pollutant contribution from local sources, a "background correction" was used. The background correction or the subtraction of the background concentration from the observed pollutant concentration is a common approach to rescale the observed concentrations to reflect the emissions from street level processes (Lenschow, et al., 2001) (De Nazelle, et al., 2012).

A background correction was used to understand how the $PM_{2.5}$ readings from the Plantower™ PMS5003 sensors compared to the $PM_{2.5}$ concentrations recorded at the Georgia Ambient Air Monitoring Program's site. The monitoring site is located at the Georgia Department of Transportation's Transportation Management Center (Figure 29) and records the $PM_{2.5}$ concentration every hour. This concentration is considered the most representative PM concentration in the metro-Atlanta area.

4.2.5.2 Route Segmentation

In order to summarize the findings from all the runs during the data collection period, researchers divided the routes into segments and computed the average difference from the background $PM_{2.5}$ concentration for each segment. The 27 runs resulted in over

24,000 observed $PM_{2.5}$ concentrations. The data points were summarized into 138 segments. Each route has approximately 30 segments and was ridden at least five times during the data collection period resulting in a total sample size of 900 segments (n=900).

A few factors were considered to break the routes into segments including intersection locations, infrastructure types, and inclusion of an appropriate number of data points. Segments were to be long enough to include a representative sample that would mask outliers, but not so long that elevated $PM_{2.5}$ concentrations would be overlooked. Hot spots were identified by mapping all the data simultaneously and determining where there were greater differences than the surrounding points. Data points were only assigned to one segment to avoid skewing the data.

4.2.5.3 Segment Characteristics

Researchers then assigned each route segment a type of cycling infrastructure. Though there is significant variation in the available cycling infrastructure, researchers identified four categorizes that encompass all segments of the routes. The four categories are (1) shared lane, (2) bike lane, (3) buffered or protected bike lane, and (4) separated path or trail. The buffered or protected bike lane was distinguished from the bike lane by having a physical barrier (i.e. pavement striping, bollards) between the cyclists and motorized vehicles. Additionally, the buffered bike lane was distinguished from trail by being adjacent to a roadway. Whereas, trails were not directly adjacent to vehicle travel lanes.

Each segment was assigned a number one through four that corresponds to the type of cycling infrastructure. Characteristics of the cycling infrastructure were also noted. For example, researchers measured the perpendicular distance from the center of the nearest travel lane to the center of the bike lane to represent proximity to traffic. If a segment was identified as (1) in-street, cyclists' distance to traffic was documented as two feet. Segments that were identified as (4) separated paths or trails were documented as being 100 feet from traffic to represent significant separation from the roadway.

As identified in the literature review, traffic volumes and land use of the surrounding area greatly impact air quality. Therefore, a similar process was used to assign roadway functional classification and land use categories to each segment. Each segment was assigned a number one through four to represent the roadway functional classification as indicated by GDOT's road and traffic database. The four classifications are (1) arterial, (2) collector, (3) local, and (4) non-road. Non-road classifications were assigned to segments in parks. Each segment was also assigned a number one through three to reflect the land use of the area surrounding the segment. The three categories of land use are (1) commercial, (2) residential, and (3) green space.

4.3 Results

In order to summarize the findings from this study, researchers created $PM_{2.5}$ exposure maps, box plots, and linear regression models that represent the $PM_{2.5}$ concentrations collected by the low-cost air quality sensors.

4.3.1 $PM_{2.5}$ Exposure Maps

Figure 34 shows the average difference of the background $PM_{2.5}$ concentration from the observed $PM_{2.5}$ concentrations along the four routes. The four routes had few segments that recorded air quality worse than the background concentration. During most of the routes, riders experienced air quality that was better than the air quality recorded at the monitoring site. There were specific segments that riders were exposed to higher $PM_{2.5}$ concentrations. However, given that the cyclist remained in motion, the time spent along each of the segments was minimal. Descriptive statistics for each route are provided in Table 2. It is important to note that a single background concentration was used to correct the recorded $PM_{2.5}$ concentrations as described in Section 4.2.5.1 Background Correction.

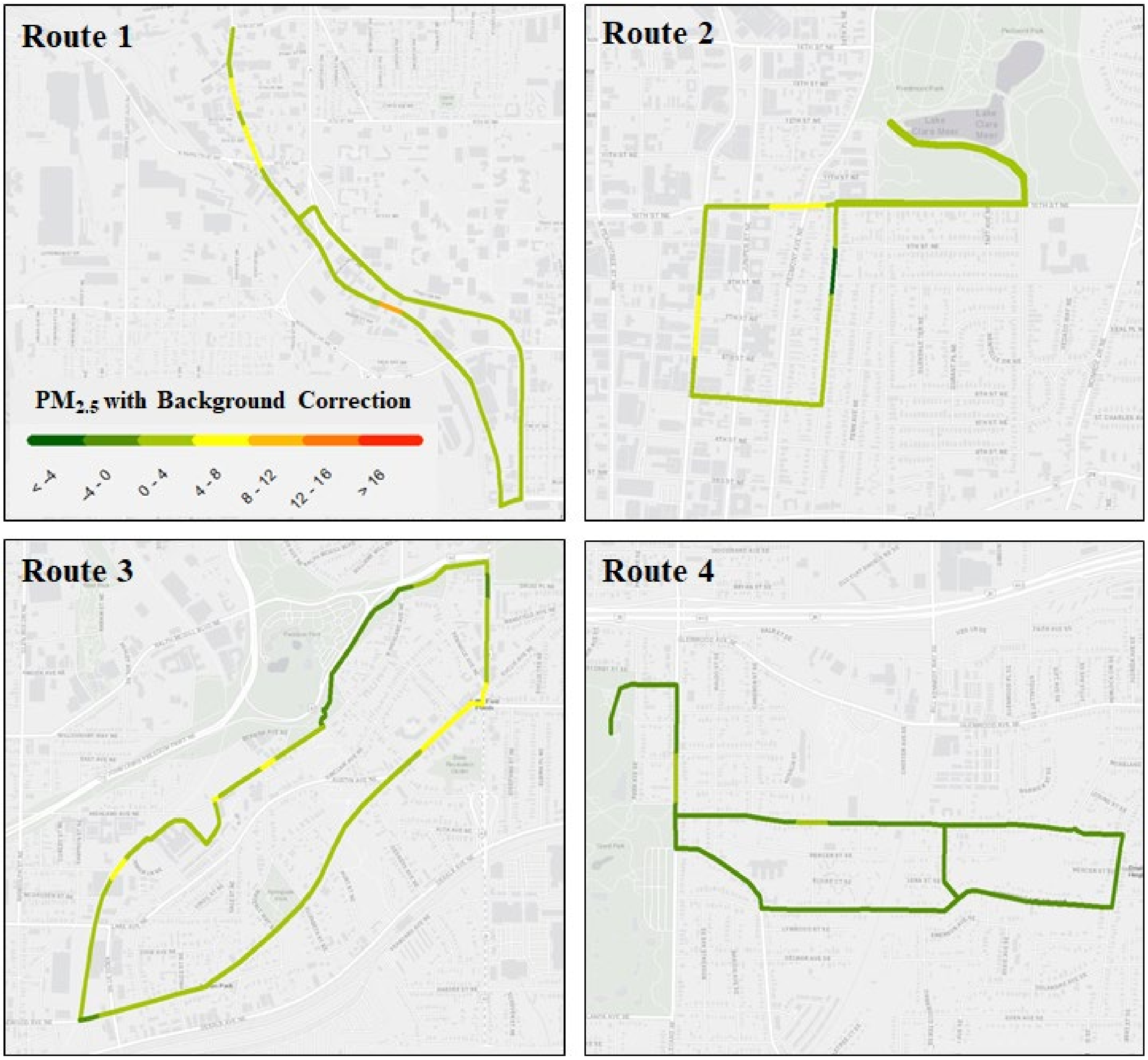

Figure 34 - $PM_{2.5}$ exposure maps corrected for background concentration; the $PM_{2.5}$ concentrations are the average of all runs on the route segments.

Table 2 - Descriptive statistics for routes using segmented data.

Route	Average $PM_{2.5}$ (µg/m³)	Minimum $PM_{2.5}$ (µg/m³)	Maximum $PM_{2.5}$ (µg/m³)	Standard Deviation
With Background Correction				
1	1.82	-5.48	18.96	4.18
2	2.42	-5.22	25.75	3.83
3	2.17	-6.56	13.72	5.17
4	-1.26	-5.79	11.78	3.52
Without Background Correction				
1	7.60	-1.13	25.57	4.02
2	9.45	1.00	32.95	4.55
3	8.53	1.24	22.86	5.67
4	3.80	-1.19	16.88	3.24

As described in Section 4.2.5: Data Analysis, the routes were divided into segments based on intersection locations, infrastructure types, and inclusion of an appropriate number of data points. Figure 35 through Figure 38 show the average $PM_{2.5}$ concentration corrected for background concentration of each route segment with the route segments numbered. Additionally, Table 3 through Table 6 following these figures provide detailed characteristics of the route segments. The characteristics that were examined in this study include type of cycling infrastructure, number of travel lanes, speed limit, cyclists' distance from travel lane (shown as "Distance" in the following tables), GDOT's roadway functional classification (FC), and land use of the surrounding area.

The characteristics of the route segments in conjunction with the meteorological conditions during each run documented in Table 1 were used to identify patterns about which types of cycling infrastructure are better or worse for cyclists' health based on the data collected with the low-cost air quality sensors.

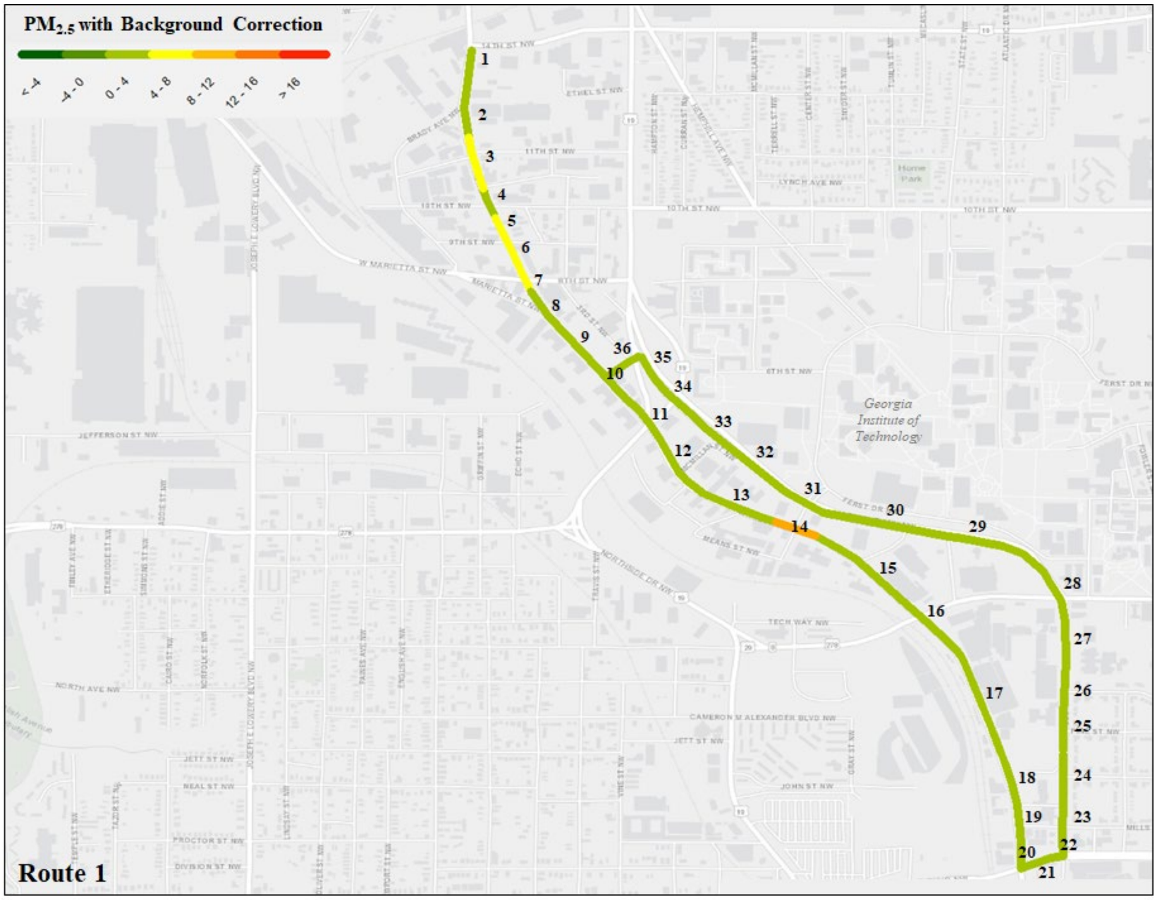

Figure 35 - Average $PM_{2.5}$ concentration corrected for background concentration along Route 1 with route segments numbered.

Table 3 - Overview of Route 1 segments and their characteristics.

Segment	Average $PM_{2.5}$ ($\mu g/m^3$)	Type of Cycling Infrastructure	Number of Travel Lanes	Speed Limit (mph)	Distance (ft.)	GDOT FC	Land Use
1	1.98	1	3	35	2.0	1	1
2	2.81	1	3	35	2.0	1	1
3	4.23	1	3	35	2.0	1	1
4	3.14	1	3	35	2.0	1	1
5	4.67	1	3	35	2.0	1	1
6	5.52	1	3	35	2.0	1	1
7	4.37	1	3	35	2.0	1	1
8	3.62	1	3	35	2.0	1	1
9	2.39	1	4	35	2.0	1	1
10	2.69	2	3	35	6.7	1	1
11	3.81	2	3	35	6.7	1	1
12	2.40	2	3	35	6.7	1	1
13	1.14	2	3	35	6.7	1	1
14	8.10	2	3	35	6.7	1	1
15	0.86	2	3	35	6.7	1	1
16	1.75	2	3	35	6.7	1	1
17	0.93	2	3	35	6.7	1	1
18	1.14	2	3	35	6.7	1	1
19	1.60	2	3	35	6.7	1	1
20	1.05	2	3	35	6.7	1	1
21	0.53	2	4	35	7.5	1	1
22	0.80	2	5	35	7.5	1	1
23	1.31	3	3	35	19.3	2	1
24	0.50	3	3	35	19.3	2	1
25	1.16	3	3	35	19.3	2	1
26	0.73	3	3	35	13.0	2	1
27	1.19	3	4	35	10.2	2	1
28	1.15	3	2	25	31.0	2	3
29	2.71	3	2	25	31.0	2	3
30	3.05	3	2	25	32.0	2	3
31	2.00	3	2	25	26.0	2	3
32	2.44	3	2	25	26.0	2	3
33	3.02	3	2	25	36.0	2	3
34	2.38	3	2	25	36.0	2	3
35	2.40	3	2	25	62.0	2	2
36	1.07	1	2	25	2.0	3	2

Type of Cycling Infrastructure: 1 – shared lane, 2 – bike lane, 3 – buffered bike lane, 4 - trail
GDOT FC: 1 – arterial, 2 – collector, 3 – local, 4 – non-road
Land Use: 1 – commercial, 2 – residential, 3 – green space

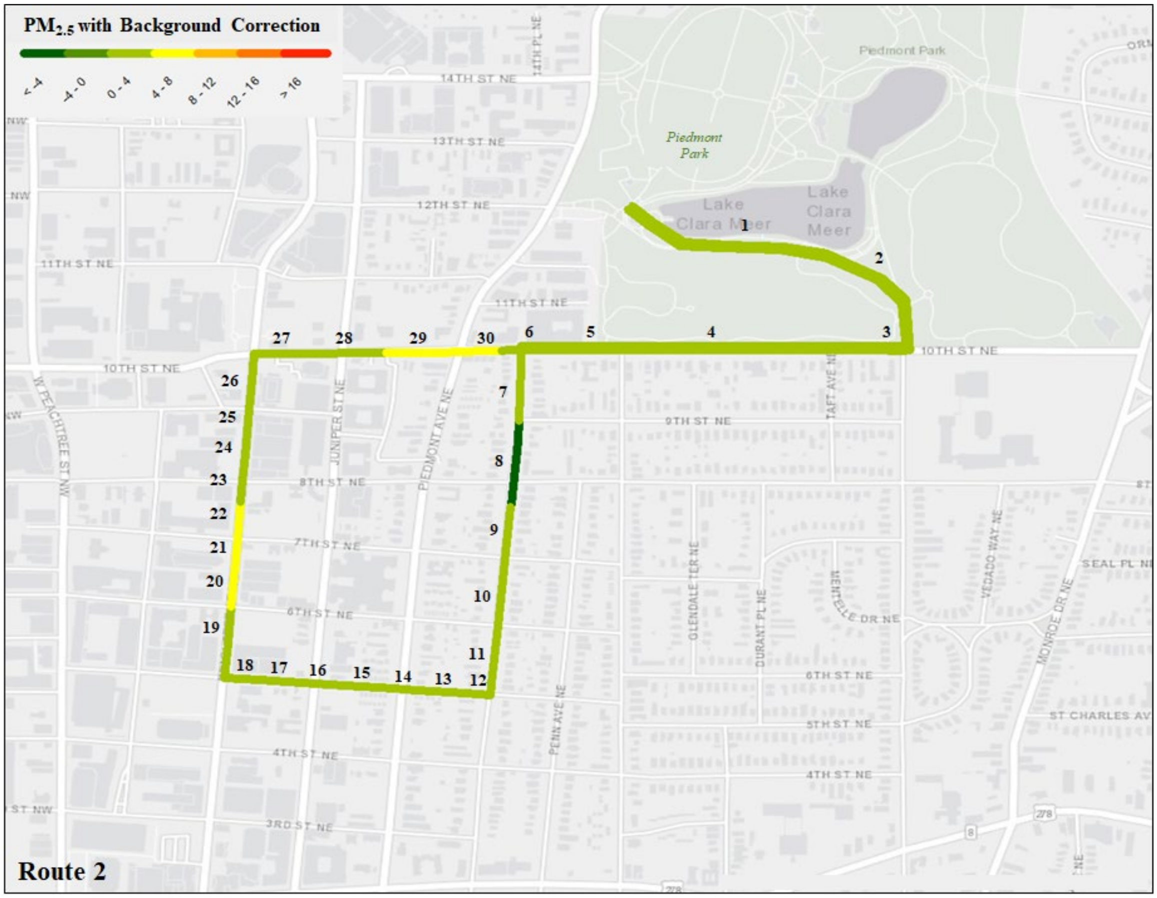

Figure 36 - Average $PM_{2.5}$ concentration corrected for background concentration along Route 2 with route segments numbered.

Table 4 - Overview of Route 2 segments and their characteristics.

Segment	Average $PM_{2.5}$ ($\mu g/m^3$)	Type of Cycling Infrastructure	Number of Travel Lanes	Speed Limit (mph)	Distance (ft.)	GDOT FC	Land Use
1	0.70	4	0	N/A	100.0	4	3
2	0.70	4	0	N/A	100.0	4	3
3	1.69	3	3	35	12.0	1	2
4	1.17	3	3	35	12.0	1	2
5	1.46	3	3	35	12.0	1	2
6	1.02	3	3	35	12.0	1	2
7	2.87	1	2	25	2.0	3	2
8	-0.12	1	2	25	2.0	3	2
9	0.94	1	2	25	2.0	3	2
10	1.19	1	2	25	2.0	3	2
11	0.76	1	2	25	2.0	3	2
12	1.46	1	2	25	2.0	3	2
13	1.83	1	2	25	2.0	3	2
14	1.17	1	2	25	2.0	3	2
15	2.40	2	2	25	7.8	3	2
16	0.71	2	2	25	7.8	3	2
17	2.78	2	2	25	7.8	3	2
18	2.59	2	2	25	7.8	3	2
19	1.68	1	4	35	2.0	1	1
20	4.96	1	4	35	2.0	1	1
21	6.29	1	4	35	2.0	1	1
22	5.34	1	4	35	2.0	1	1
23	1.73	1	4	35	2.0	1	1
24	1.73	1	4	35	2.0	1	1
25	0.56	1	4	35	2.0	1	1
26	2.83	1	4	35	2.0	1	1
27	3.49	1	4	35	2.0	1	1
28	1.93	1	4	35	2.0	1	1
29	4.39	1	4	35	2.0	1	1
30	6.14	1	4	35	2.0	1	1

Type of Cycling Infrastructure: 1 – shared lane, 2 – bike lane, 3 – buffered bike lane, 4 - trail
GDOT FC: 1 – arterial, 2 – collector, 3 – local, 4 – non-road
Land Use: 1 – commercial, 2 – residential, 3 – green space

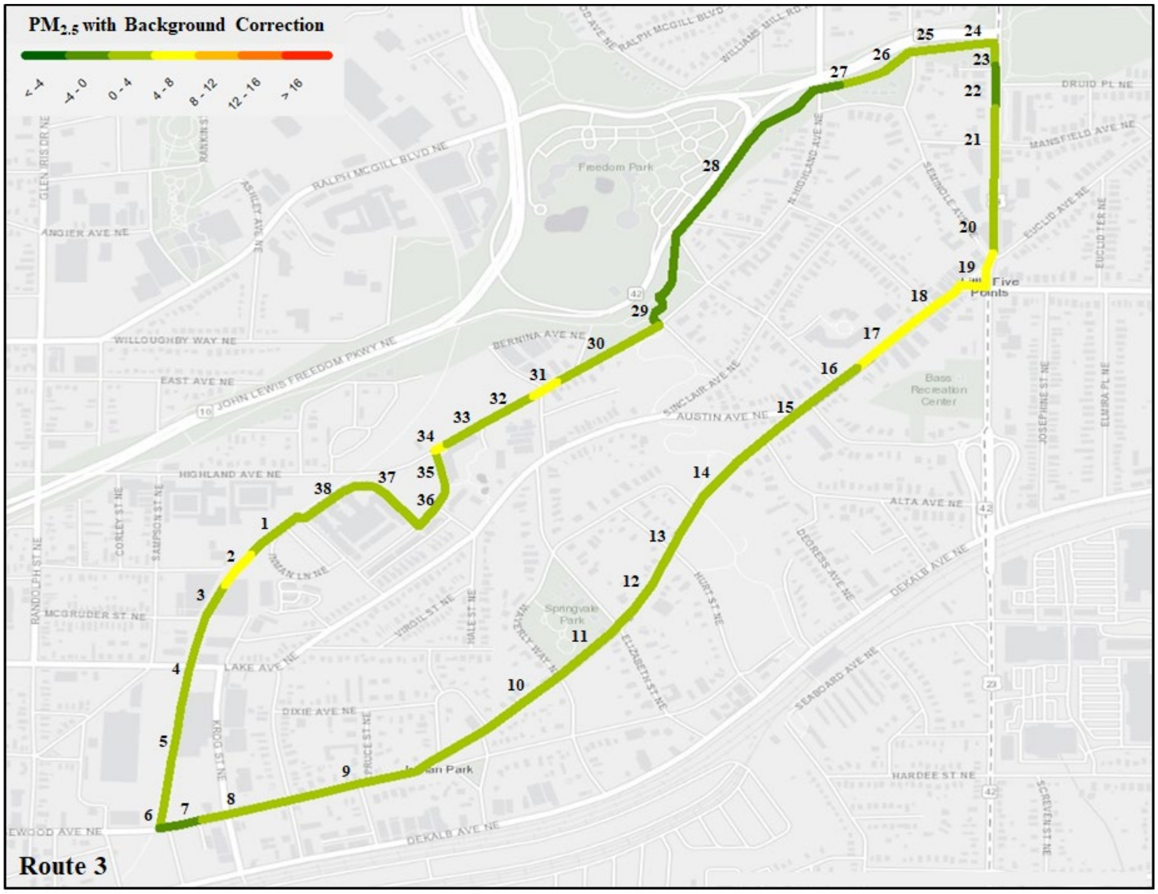

Figure 37 - Average $PM_{2.5}$ concentration corrected for background concentration along Route 3 with route segments numbered.

Table 5 - Overview of Route 3 segments and their characteristics.

Segment	Average $PM_{2.5}$ (μg/m³)	Type of Cycling Infrastructure	Number of Travel Lanes	Speed Limit (mph)	Distance (ft.)	GDOT FC	Land Use
1	2.40	4	0	N/A	100	4	3
2	4.95	4	0	N/A	100	4	3
3	1.41	4	0	N/A	100	4	3
4	0.95	4	0	N/A	100	4	3
5	3.50	4	0	N/A	100	4	3
6	2.21	4	0	N/A	100	4	3
7	-0.95	2	2	35	8.3	1	2
8	1.67	2	2	35	8.3	1	2
9	2.54	1	2	25	2.0	1	2
10	2.20	1	2	25	2.0	1	2
11	1.93	1	2	25	2.0	1	2
12	1.26	1	2	25	2.0	1	2
13	0.76	1	2	25	2.0	1	2
14	2.75	1	2	25	2.0	1	2
15	2.56	1	2	25	2.0	1	2
16	1.14	1	2	25	2.0	1	1
17	4.43	1	2	25	2.0	1	1
18	4.97	1	2	25	2.0	1	1
19	4.10	1	4	35	2.0	1	1
20	0.94	2	4	35	7.4	1	1
21	1.84	2	4	35	7.4	1	1
22	-0.14	2	4	35	7.4	1	2
23	1.01	2	4	35	7.4	1	1
24	0.12	4	0	N/A	100	1	3
25	3.95	4	0	N/A	100	1	3
26	1.73	4	0	N/A	100	1	3
27	-3.85	4	0	N/A	100	1	3
28	-3.79	4	0	N/A	100	1	3
29	1.55	4	0	N/A	100	2	3
30	1.64	1	2	25	2.0	2	1
31	4.40	1	2	25	2.0	2	1
32	3.27	1	2	25	2.0	2	1
33	3.06	1	2	25	2.0	2	1
34	4.08	1	2	25	2.0	2	1
35	0.34	1	2	25	2.0	3	2
36	1.46	1	2	25	2.0	3	2
37	0.91	1	2	25	2.0	3	2
38	2.04	1	2	25	2.0	3	2

Type of Cycling Infrastructure: 1 – shared lane, 2 – bike lane, 3 – buffered bike lane, 4 - trail
GDOT FC: 1 – arterial, 2 – collector, 3 – local, 4 – non-road
Land Use: 1 – commercial, 2 – residential, 3 – green space

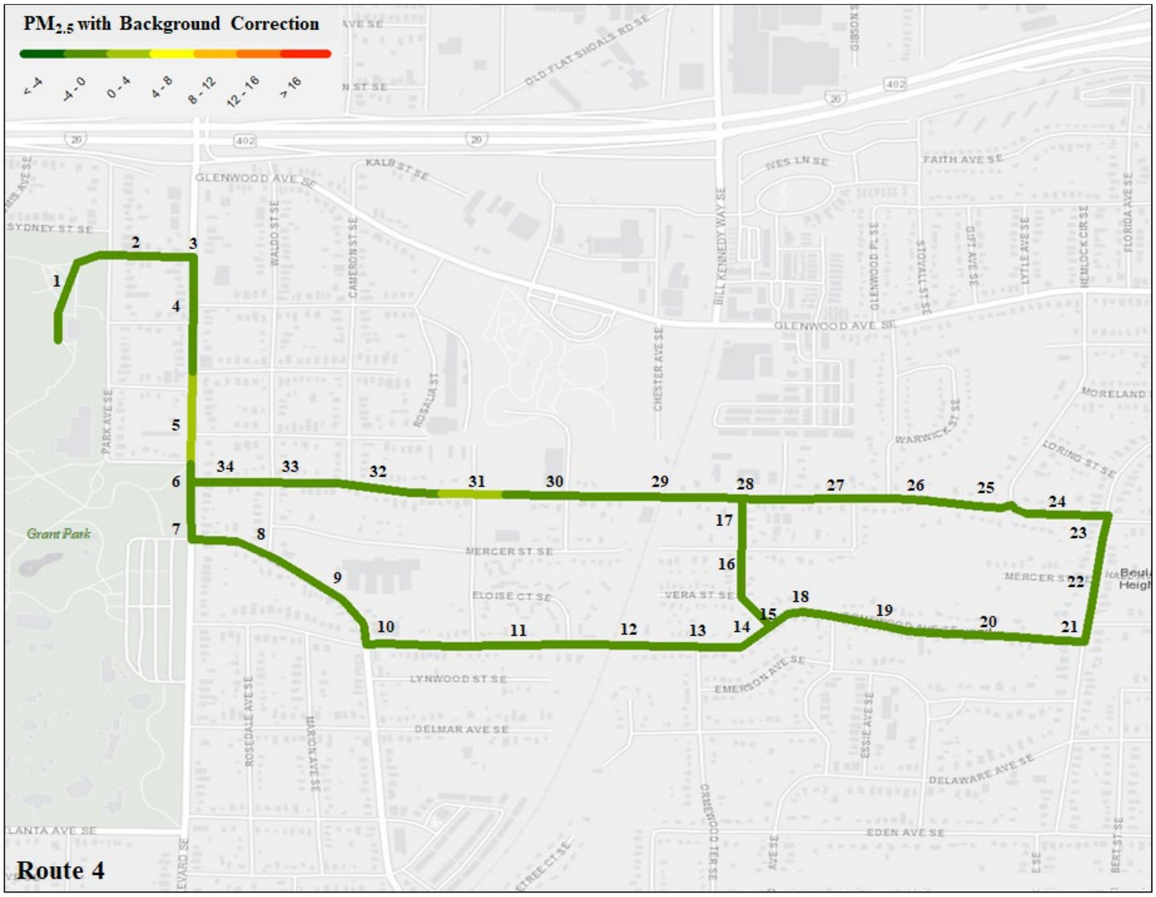

Figure 38 - Average $PM_{2.5}$ concentration corrected for background concentration along Route 4 with route segments numbered.

Table 6 - Overview of Route 4 segments and their characteristics.

Segment	Average $PM_{2.5}$ ($\mu g/m^3$)	Type of Cycling Infrastructure	Number of Travel Lanes	Speed Limit (mph)	Distance (ft.)	GDOT FC	Land Use
1	-1.14	4	0	N/A	100.0	4	3
2	-2.42	1	2	25	2.0	2	2
3	-1.45	1	2	25	2.0	2	2
4	-1.38	1	4	35	2.0	1	1
5	0.28	1	4	35	2.0	1	1
6	-1.52	1	4	35	2.0	1	1
7	-2.76	1	4	35	2.0	1	1
8	-1.89	2	2	25	7.4	2	2
9	-1.85	2	2	25	7.4	2	2
10	-2.29	3	2	25	10.0	2	2
11	-0.84	3	2	25	10.0	3	2
12	-3.86	3	2	25	10.0	3	2
13	-0.99	3	2	25	10.0	3	2
14	-1.61	3	2	25	10.0	3	2
15	-0.50	3	2	25	10.0	3	2
16	-1.41	1	2	25	2.0	3	2
17	-2.78	1	2	25	2.0	3	2
18	-1.15	3	2	25	10.0	3	2
19	-1.03	3	2	25	10.0	3	2
20	-1.62	3	2	25	10.0	3	2
21	-1.99	3	2	25	10.0	3	2
22	-1.99	1	2	25	2.0	3	2
23	-1.71	1	2	25	2.0	3	2
24	-2.21	1	2	25	2.0	2	2
25	-1.91	1	2	25	2.0	2	2
26	-1.07	1	2	25	2.0	2	2
27	-1.14	1	2	25	2.0	2	2
28	-3.32	1	2	25	2.0	2	2
29	-1.68	1	2	25	2.0	2	2
30	-1.68	1	2	25	2.0	2	2
31	3.34	1	2	25	2.0	2	2
32	-2.02	1	2	25	2.0	2	2
33	-0.95	1	2	25	2.0	2	2
34	-2.09	1	2	25	2.0	2	2

Type of Cycling Infrastructure: 1 – shared lane, 2 – bike lane, 3 – buffered bike lane, 4 - trail
GDOT FC: 1 – arterial, 2 – collector, 3 – local, 4 – non-road
Land Use: 1 – commercial, 2 – residential, 3 – green space

4.3.2 $PM_{2.5}$ Exposure and Segment Characteristics

The characteristics of the route segments in conjunction with the meteorological conditions during each run were used to identify patterns about which types of cycling infrastructure are better or worse for cyclists' health based on the data collected with the low-cost air quality sensors. In order to evaluate the performance of these low-cost air quality sensors, researchers had to analyze the collected data and compare the findings from this experiment to the findings from other instrumented bicycle studies.

As presented in the literature review, there were a few other studies that used an instrumented bicycle to monitor air quality. Based on the findings from these studies and other known behaviors of $PM_{2.5}$, it was hypothesized that cyclists would be exposed to lower $PM_{2.5}$ concentrations on trails and separated cycling infrastructure than on shared lanes. Cyclists were also expected to experience better air quality on local residential roads than on high volume arterials. These hypotheses were tested by creating a series of box plots. The box plots of type of cycling infrastructure (Figure 39), GDOT functional classification (Figure 40), and land use (Figure 41) reveal a few patterns about the built environment and air quality. The shaded regions of the box plots indicate observed $PM_{2.5}$ concentrations that were less than 10 $\mu g/m^3$. The World Health Organization states that long-term $PM_{2.5}$ exposure exceeding 10 $\mu g/m^3$ is associated with an increase in the long-term risk of cardiopulmonary mortality (WHO, 2013).

First, as shown in Figure 39, segments representing shared lanes had the greatest variability and highest median $PM_{2.5}$ concentration. Segments representing buffered bike lanes had the lowest median, however, the medians among the four categories did not differ as much as expected. The distribution of the trail segments closely resembles that of the bike lane segments. Overall, the segments representing buffered or separated bike lanes had the lowest interquartile values for $PM_{2.5}$ concentrations.

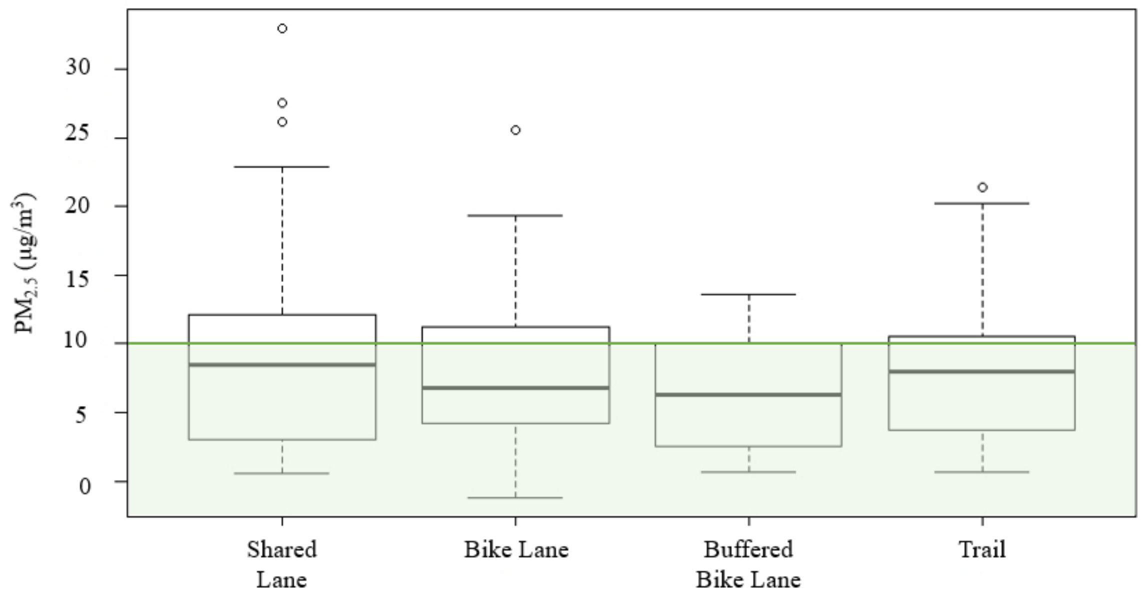

Figure 39 - Box plot of segmented $PM_{2.5}$ concentrations by type of cycling infrastructure.

As expected, arterial segments had the highest interquartile concentrations and the highest median $PM_{2.5}$ concentration (Figure 40). Minimum and upper quartile concentrations appear to be similar among the four functional classifications with the exception of collector roads. Collector roads had lower interquartile and a lower median $PM_{2.5}$ concentrations than the other three functional classifications.

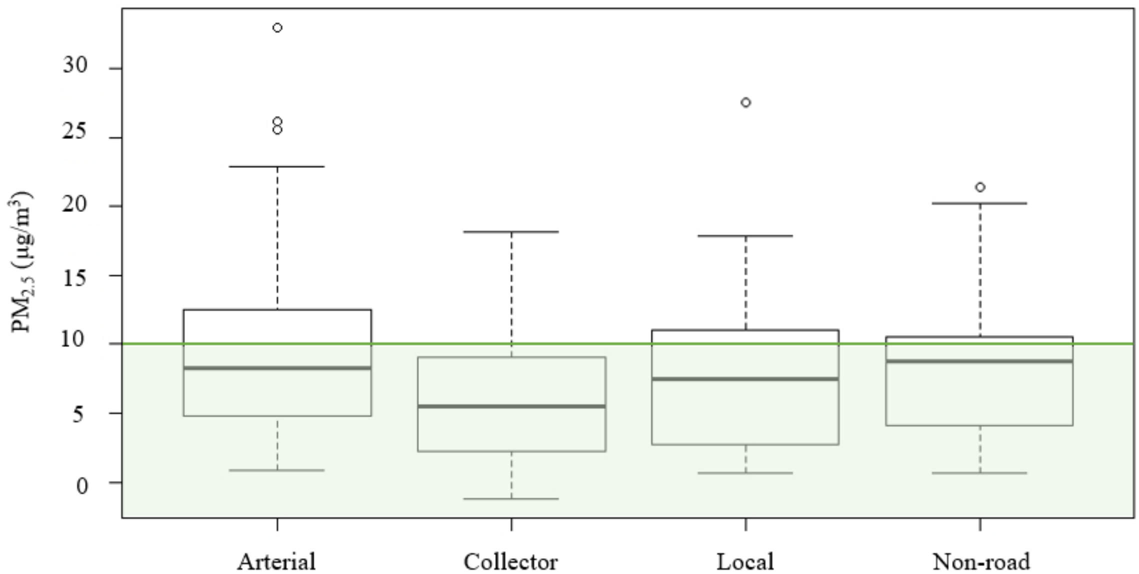

Figure 40 - Box plot of segmented $PM_{2.5}$ concentrations by GDOT functional classification.

The relationship between land use and collected $PM_{2.5}$ concentrations was also examined (Figure 41). Segments surrounded by commercial land uses had the highest interquartile concentrations and the highest variability amongst the collected $PM_{2.5}$ concentrations. Whereas, segments in residential areas had the lowest interquartile concentrations.

"Green space" was exclusively assigned to segments that were located within a park. It is important to note that there were only a few segments that were categorized as green space and therefore the higher interquartile concentrations may have resulted from factors other than surrounding land use.

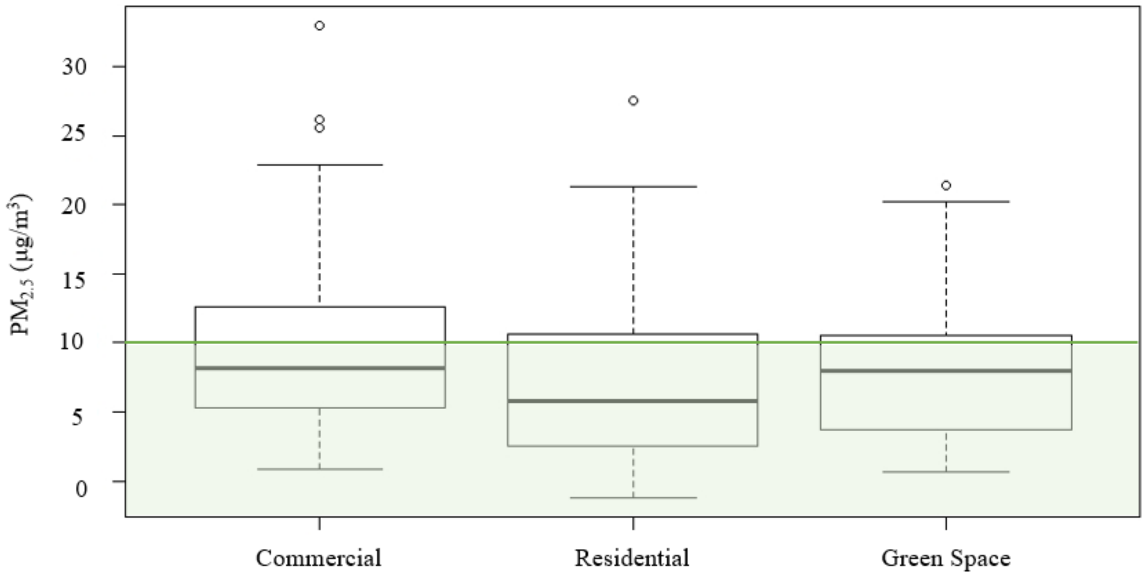

Figure 41 - Box plot of segmented $PM_{2.5}$ concentrations by land use.

To further explore the relationship between segment characteristics and $PM_{2.5}$, box plots were created using dummy variables instead of categorical variables. The following box plots show the resulting $PM_{2.5}$ concentrations for segments with and without cycling infrastructure (Figure 42), for minor and major road segments (Figure 43), and for commercial and other land uses (Figure 44).

Simplifying the categorical variables resulted in more conclusive findings. As shown in Figure 42, segments without cycling infrastructure recorded higher $PM_{2.5}$ concentrations. However, $PM_{2.5}$ concentrations for segments with cycling infrastructure are still within the interquartile concentrations of segments without cycling infrastructure. Segments along major roads (i.e. arterials and collectors) reported similar $PM_{2.5}$ concentrations as segments along minor roads (i.e. local roads and non-roads). Previous studies found that exposure was higher on high-traffic roads, however, that pattern was not shown in this data set.

Segments surrounded by commercial land uses reported higher $PM_{2.5}$ concentrations. These findings are in alignment with previous research that suggested that exposure was higher in areas of commercial and industrial land use. Land use showed to be a significant indicator of cyclists' exposure to $PM_{2.5}$.

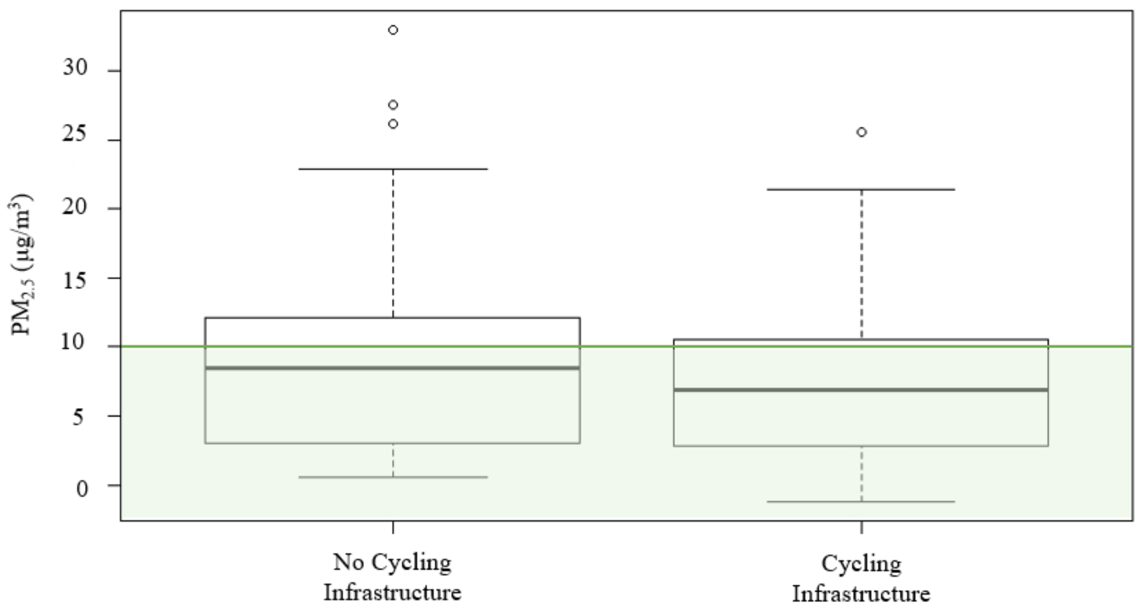

Figure 42 - Box plot of segmented $PM_{2.5}$ concentrations by presence of cycling infrastructure.

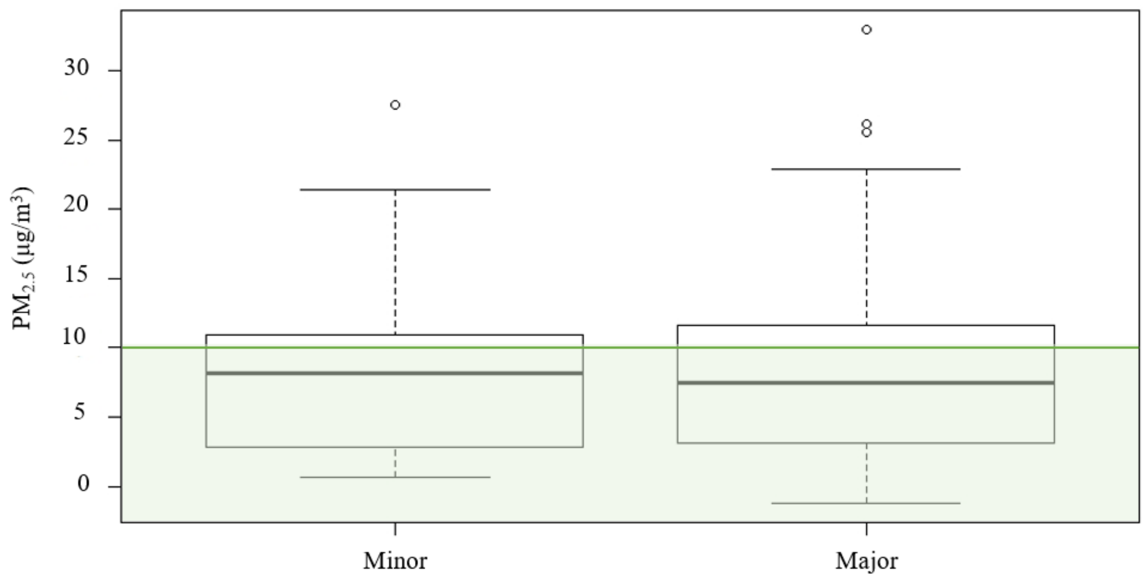

Figure 43 - Box plot of segmented $PM_{2.5}$ concentrations for minor and major roads.

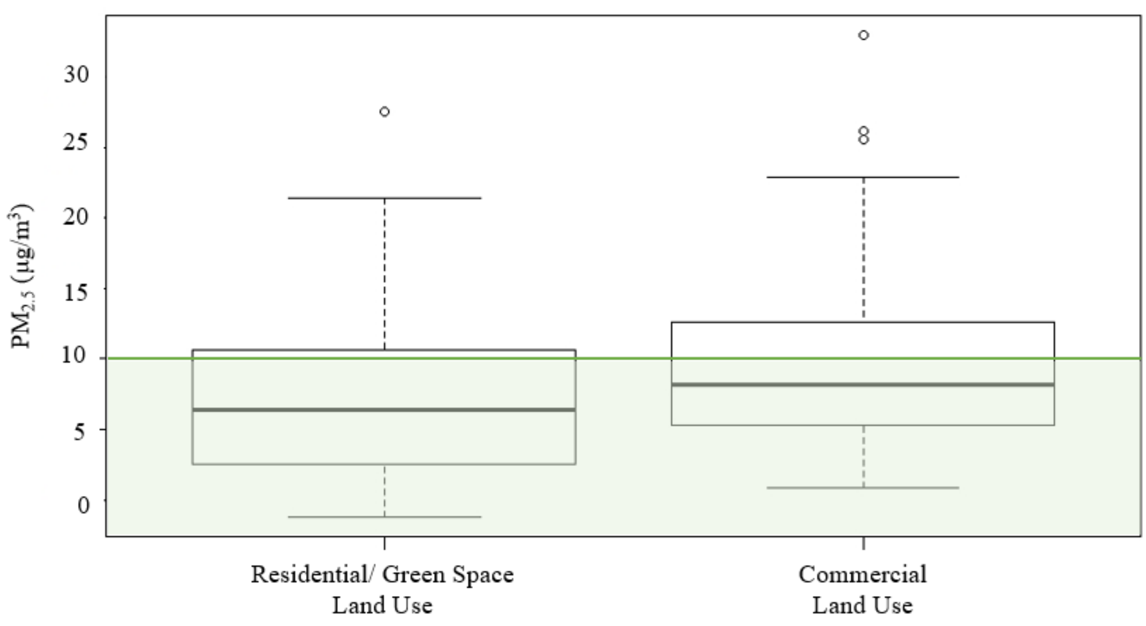

Figure 44 - Box plot of segmented $PM_{2.5}$ concentrations for other land uses and commercial land use.

4.3.3 Regression Analysis

Linear regression models were created to further examine the relationship among segment characteristics and $PM_{2.5}$ concentrations. Recorded $PM_{2.5}$ concentrations, the difference between $PM_{2.5}$ and the urban background concentration, and the difference between $PM_{2.5}$ concentrations and the average $PM_{2.5}$ concentration during the specific run were all modeled. These models are tools used to identify relationships among the examined variables, but they are not predictive models. They are not intended to predict near roadway $PM_{2.5}$ concentrations.

Standard linear regression models rely on the following assumptions: the distribution of the sample means is normal (normality), errors of the explanatory variables have constant variance (homoscedasticity), errors of the explanatory variables are uncorrelated with each other (independence of errors), and the explanatory variables are not intercorrelated with each other (lack of perfect multicollinearity) (Mokhatarian, 2019).Violations of these assumptions can be identified with the appropriate statistical tests.

According to the Shapiro-Wilk test of normality, the collected data does violate the assumption of normality with a p-value (p-value=2.20e-16) of less than 0.05, indicating to reject the null hypothesis that the data are from a normally distributed population. Violating the assumption of normality can be remedied by transforming the dependent variable, observed $PM_{2.5}$ concentrations. Common transformations include taking the natural log or square root of the dependent variable. Additionally, the assumption of homoscedasticity is violated as indicated by the results of the Breusch-Pagan test. Similar to the remedies for violating normality, violating homoscedasticity can be addressed by transforming the dependent variable or the explanatory variables that contribute to heteroscedasticity. Heteroscedastic-consistent standard errors can also be applied (Mokhatarian, 2019). The other assumptions of standard linear regression models are not violated and multicollinearity issues were addressed by removing variables as described in the following section.

The linear regression models incorporate both run and route characteristics. Many different variables were considered for the model shown in Table 7. In the final iterations of the model, variables, such as number of travel lanes, speed limit, and distance from traffic were omitted, because they were co-linear with other variables. The variables, type of cycling infrastructure, functional classification, and land use, accounted for these variables in the final iterations of the model. Traffic volumes, though a major explanatory variable of particulate matter exposure, were not recorded. However to compensate for traffic volumes, variables, such as functional classification were used. It is suspected that functional classification would indicate if a route segment had high or low traffic volumes without having the exact traffic counts for each day of data collection.

Table 7 - Descriptive statistics for variables considered.

Variable	Units	Average	Minimum	Maximum
Time of Day	Categorical	2.78	1	3
Day of Week	Categorical	2.01	1	6
Weekday or Weekend	Dummy	0.84	0	1
Temperature	°F	54.89	33	81
Wind Speed	mph	10.96	0	23
Relative Humidity	%	42.70	13	86
Type of Cycling Infrastructure	Categorical	1.83	1	4
Number of travel lanes	lanes	2.45	0	5
Speed Limit	mph	26.77	0	35
Distance from Travel Lane	feet	15.44	2	100
Functional Classification	Categorical	1.91	1	4
Land Use	Categorical	1.66	1	3

4.3.3.1 $PM_{2.5}$ Concentrations

Table 8 shows the variables and resulting coefficients of an iteration of the model for the $PM_{2.5}$ concentrations recorded with the low-cost air quality sensors. The model includes meteorological variables, because temperature, wind speed, and humidity varied significantly among the runs and are known to greatly impact $PM_{2.5}$ concentrations.

The coefficients for type of cycling infrastructure, functional classification, and land use have the expected signs. The coefficients for type of cycling infrastructure, functional classification and land use are all negative. The negative signs indicate that cyclists' $PM_{2.5}$ exposure was lower on separated cycling infrastructure (i.e. buffered bike lanes and trails) and in residential areas and in green space. However, type of cycling infrastructure and functional classification were insignificant in comparison to other variables, such as land use. Land use, specifically if the segment was in a commercial area, was found to be one of the most significant indicators of cyclists' $PM_{2.5}$ exposure. Segments identified as areas of commercial land use had higher $PM_{2.5}$ concentrations than segments in residential areas or in parks.

Whether the run took place on a weekday or on a weekend was also found to be a significant indicator of cyclist's $PM_{2.5}$ exposure. As expected, runs that occurred on a weekday during typical traffic patterns recorded higher $PM_{2.5}$ concentrations. Whereas, weekend runs recorded much lower $PM_{2.5}$ concentrations.

Table 8 - Linear Regression for $PM_{2.5}$ with categorical variables (n=900, R_2=0.230).

Variable	Units	Coefficient		P
Intercept	N/A	2.27	•	0.075
Weekday or Weekend	Dummy	3.25	***	<0.001
Time of Day	Dummy	-0.31		0.112
Temperature	°F	0.03	*	0.043
Wind Speed	mph	-0.11	***	<0.001
Relative Humidity	%	0.12	***	<0.001
Type of Cycling Infrastructure	Categorical	-0.05		0.771
Functional Classification	Categorical	-0.01		0.951
Land Use	Categorical	-1.14	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

Another iteration of the model used dummy variables instead of categorical variables to represent the segment characteristics. This model investigated if the presence of any type of cycling infrastructure had a significant impact on cyclists' exposure. The model in Table 9 shows that the dummy variables for segment characteristics (i.e. cycling infrastructure, minor or major road, commercial land use) were all significant. The coefficients for the segment characteristics have the expected signs. The coefficients for cycling infrastructure and major or minor road are negative. The negative signs indicate that $PM_{2.5}$ concentrations were lower where cycling infrastructure was present and on minor roads (i.e. local and non-road segments). The coefficient for commercial land use is positive indicating that segments identified in areas of commercial land use recorded higher $PM_{2.5}$ concentrations than segments in residential or in green space land use.

Table 9 - Linear Regression for $PM_{2.5}$ with dummy variables (n=900, R_2=0.259).

Variable	Units	Coefficient		P
Intercept	N/A	-0.17		0.898
Weekday or Weekend	Dummy	3.33	***	<0.001
Time of Day	Dummy	-0.23		0.215
Temperature	°F	0.04	*	0.012
Wind Speed	mph	-0.12	***	<0.001
Relative Humidity	%	0.12	***	<0.001
Cycling Infrastructure	Dummy	-0.58	•	0.056
Minor or Major Road	Dummy	-1.36	***	<0.001
Commercial Land Use	Dummy	2.72	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

The final iteration of this model for the $PM_{2.5}$ concentrations recorded with the low-cost air quality sensors (Table 10) has dummy variables for each type of cycling infrastructure. The coefficients for bike lane, buffered bike lane, and trail are all negative, indicating that each type recorded lower $PM_{2.5}$ concentrations than the base type, shared lane. However, the magnitude of these coefficients are not in the expected order. It was predicted that trail would have the largest negative coefficient. The absolute value of the coefficient is smaller than the absolute values of the coefficients for bike lane and buffered bike lane. However, trail and bike lane were not significant, whereas buffered bike lane was significant.

Table 10 - Linear Regression for $PM_{2.5}$ with dummy variables (n=900, R_2=0.264).

Variable	Units	Coefficient		P
Intercept	N/A	-0.35		0.785
Weekday or Weekend	Dummy	3.37	***	<0.001
Time of Day	Dummy	-0.25		0.189
Temperature	°F	0.04	**	0.007
Wind Speed	mph	-0.11	***	<0.001
Relative Humidity	%	0.11	***	<0.001
Bike Lane	Dummy	-0.54		0.181
Buffered Bike Lane	Dummy	-1.08	**	0.006
Trail	Dummy	-0.41		0.439
Minor or Major Road	Dummy	-1.24	***	<0.001
Commercial Land Use	Dummy	2.80	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

It was unexpected that if the variable "trail" was insignificant in the models. Route segments that were significantly separated (approximately 100 feet) from vehicle roadways were identified as trails. Examples of trails include the Atlanta BeltLine and Freedom Park Trail (Route 3). Because so few segments (n=90) met this criteria, a correlation matrix was created to examine if the variable "trail" correlated with any of the other variables in the model. Table 11 shows the resulting correlation matrix for the variables used in the linear regression models.

Route segments identified as trails did not appear to correlate significantly with the other variables. The greatest correlation was between trail and commercial land use. In Atlanta, many trails traverse commercial areas that are populated with shops and restaurants that attract those using the trails for recreation. According to the models, land use was a more significant indicator of cyclists' $PM_{2.5}$ exposure than riding on a trail or multi-use path.

Table 11 - Correlation matrix for variables used in linear regression models.

	Time of Day	Weekday or Weekend	Temp.	WS	RH	Bike Lane	Buffered Bike Lane	Trail	Major or Minor Road	Commercial Land Use
Time of Day										
Weekday or Weekend	0.03									
Temp.	-0.14	0.11								
WS	0.02	-0.11	-0.06							
RH	0.05	0.08	-0.42	0.04						
Bike Lane	-0.14	-0.1	-0.03	0.01	0.05					
Buffered Bike Lane	-0.11	-0.04	0.1	0.02	-0.09	-0.21				
Trail	0.07	0	-0.08	-0.09	0.12	-0.15	-0.16			
Major or Minor Road	-0.18	-0.13	0	-0.05	0.05	0.01	0.05	-0.24		
Commercial Land Use	-0.29	-0.19	-0.07	0.05	0.08	0.08	-0.07	-0.29	0.61	

4.3.3.2 $PM_{2.5}$ Concentrations Corrected for Background Concentration

The same iterations of the model were repeated to model $PM_{2.5}$ concentrations corrected for background concentration. Table 12 shows the variables and resulting coefficients of the first iteration of the model for $PM_{2.5}$ corrected for background concentration. The coefficients for type of cycling infrastructure and land use have the expected signs. The coefficients for type of cycling infrastructure and land use are negative. The negative signs indicate that cyclists' $PM_{2.5}$ exposure was lower on separated cycling infrastructure (i.e. bike lanes, buffered bike lanes, and trails) and in residential areas and in green space. The coefficient for functional classification was expected to be negative indicating that local or non-road segments reported better air quality than high-traffic arterial and collector roads. However, the coefficient is relatively small and was found to be insignificant.

Both functional classification and type of cycling infrastructure were insignificant in comparison to other variables, such as land use. Land use, specifically if the segment was in a commercial area, was found to be one of the most significant indicators of cyclists' $PM_{2.5}$ exposure. Segments identified as areas of commercial land use recorded higher $PM_{2.5}$ concentrations.

Table 12 - Linear Regression for $PM_{2.5}$ corrected for background concentration with categorical variables (n=900, R^2=0.223).

Variable	Units	Coefficient		P
Intercept	N/A	1.11		0.329
Weekday or Weekend	Dummy	0.93	*	0.013
Time of Day	Dummy	-0.28	**	0.010
Temperature	°F	-0.005	•	0.072
Wind Speed	mph	-0.20	•	0.083
Relative Humidity	%	0.10	***	<0.001
Type of Cycling Infrastructure	Categorical	-0.10		0.521
Functional Classification	Categorical	0.10		0.546
Land Use	Categorical	-1.10	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

The second iteration of the model for $PM_{2.5}$ concentrations corrected for background concentration shown in Table 13 produced the expected signs for the coefficients of the dummy variables representing segment characteristics (i.e. cycling infrastructure, minor or major road, commercial land use). The dummy variables for segment characteristics were also all significant.

The coefficients for cycling infrastructure and major or minor road are negative. The negative signs indicate that $PM_{2.5}$ concentrations were lower where cycling infrastructure was present and on minor roads (i.e. local and non-road segments). The coefficient for land use is positive indicating that segments identified in areas of commercial land use recorded higher $PM_{2.5}$ concentrations than segments in residential or in green space land use.

Table 13 - Linear Regression for PM2.5 corrected for background concentration with dummy variables (n=900, R_2=0.245).

Variable	Units	Coefficient		P
Intercept	N/A	-0.95		0.413
Weekday or Weekend	Dummy	0.98	**	0.008
Time of Day	Dummy	-0.25		0.146
Temperature	°F	0.001		0.951
Wind Speed	mph	-0.20	***	<0.001
Relative Humidity	%	0.10	***	<0.001
Cycling Infrastructure	Dummy	-0.64	*	0.018
Minor or Major Road	Dummy	-0.64	**	0.003
Commercial Land Use	Dummy	2.17	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

The final iteration of this model for the $PM_{2.5}$ concentrations corrected for background concentration (Table 14) has dummy variables for each type of cycling infrastructure. The coefficients for bike lane, buffered bike lane, and trail are all negative, indicating that each type recorded lower $PM_{2.5}$ concentrations than the base type, shared lane. However, the magnitude of these coefficients are not in the expected order. It was predicted that trail would have the largest negative coefficient. The absolute value of the coefficient is smaller than the absolute values of the coefficients for bike lane and buffered bike lane. However, trail was not significant, whereas bike lane and buffered bike lane were significant.

Again, land use was one of the most significant variables. The coefficient for land use is positive indicating that segments identified in areas of commercial land use recorded higher $PM_{2.5}$ concentrations than segments in residential or in green space land use.

Table 14 - Linear Regression for $PM_{2.5}$ corrected for background concentration with dummy variables (n=900, R_2=0.246).

Variable	Units	Coefficient		P
Intercept	N/A	-1.03		0.374
Weekday or Weekend	Dummy	0.99	**	0.007
Time of Day	Dummy	-0.26		0.135
Temperature	°F	0.001		0.895
Wind Speed	mph	-0.20	***	<0.001
Relative Humidity	%	0.01	***	<0.001
Bike Lane	Dummy	-0.70	•	0.057
Buffered Bike Lane	Dummy	-0.82	*	0.021
Trail	Dummy	-0.14		0.767
Minor or Major Road	Dummy	-0.98	**	0.005
Commercial Land Use	Dummy	2.23	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

4.3.3.3 Difference between $PM_{2.5}$ Concentrations and Run Average

The same iterations of the model were repeated to model the difference between the $PM_{2.5}$ concentrations and the average $PM_{2.5}$ concentration for the specific run. The intention of these models was to isolate the variables for segment characteristics by eliminating variation from meteorological conditions. It is important to note that the meteorological variables (i.e. temperature, wind speed, and relative humidity) were all insignificant in the models shown in Table 15, Table 16, and Table 17.

These models showed similar patterns as the models for $PM_{2.5}$ concentration and $PM_{2.5}$ concentration corrected for background concentration. As expected, $PM_{2.5}$ concentrations were lower where cycling infrastructure was present, on minor roads (i.e. local and non-road segments), and in residential areas and in parks.

Land use and time of day were found to be highly significant when the difference between the $PM_{2.5}$ concentrations and the average $PM_{2.5}$ concentration for the specific run. Time of day was not as significant in the models for $PM_{2.5}$ and $PM_{2.5}$ corrected for background concentration. The positive coefficient for time of day indicates that $PM_{2.5}$ concentrations were higher during afternoon runs than during morning runs.

Table 15 - Linear Regression for $PM_{2.5}$ with categorical variables (n=900, R^2=0.068).

Variable	Units	Coefficient		P
Intercept	N/A	0.08		0.894
Weekday or Weekend	Dummy	0.23		0.267
Time of Day	Dummy	0.43	***	<0.001
Temperature	°F	-0.003		0.593
Wind Speed	mph	0.002		0.879
Relative Humidity	%	0.01	*	0.050
Type of Cycling Infrastructure	Categorical	-0.14	•	0.097
Functional Classification	Categorical	0.02		0.861
Land Use	Categorical	-0.61	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

Table 16 - Linear Regression for $PM_{2.5}$ with dummy variables (n=900, R^2=0.109).

Variable	Units	Coefficient		P
Intercept	N/A	-1.36	•	0.034
Weekday or Weekend	Dummy	0.27		0.188
Time of Day	Dummy	0.45	***	<0.001
Temperature	°F	-0.001		0.877
Wind Speed	mph	0.001		0.921
Relative Humidity	%	0.009	•	0.092
Cycling Infrastructure	Dummy	-0.66	***	<0.001
Minor or Major Road	Dummy	-0.29		0.137
Commercial Land Use	Dummy	1.21	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

Table 17 - Linear Regression for $PM_{2.5}$ with dummy variables (n=900, R^2=0.118).

Variable	Units	Coefficient		P
Intercept	N/A	-1.46	•	0.023
Weekday or Weekend	Dummy	0.29		0.157
Time of Day	Dummy	0.44	***	<0.001
Temperature	°F	-0.0001		0.988
Wind Speed	mph	0.005		0.704
Relative Humidity	%	0.007		0.178
Bike Lane	Dummy	-0.81	***	<0.001
Buffered Bike Lane	Dummy	-0.82	***	<0.001
Trail	Dummy	-0.007		0.980
Minor or Major Road	Dummy	-0.23		0.232
Commercial Land Use	Dummy	1.30	***	<0.001

• Significant at 0.100
* Significant at 0.050
** Significant at 0.010
*** Significant at 0.001

4.4 Discussion of Results

This experiment was an initial study to assess the feasibility of using an instrumented bicycle equipped with low-cost air quality sensors to monitor cyclists' $PM_{2.5}$ exposure. After initial calibration, the low-cost PMS5003 sensors were determined to be appropriate for mobile air quality monitoring, although some large spikes in $PM_{2.5}$ may be missed with lower quality sensors.

Through graphical and statistical analysis, researchers found that cyclists' $PM_{2.5}$ exposure was lower on designated cycling infrastructure (i.e. bike lanes and buffered bike) and on functional classifications with lower traffic volumes (i.e. minor roads). These findings are in alignment with previous research that suggested that exposure was higher near high-traffic routes and for motorists due to their proximity to motor vehicles. Land use, specifically if the cyclist was riding through a commercial area, was found to be one of the most significant indicators of cyclists' $PM_{2.5}$ exposure. However, cyclists' $PM_{2.5}$ exposure was found to be impacted more by meteorological variables that lead the background concentration to be higher along the entire route than the proximity to vehicles at specific points along the route.

There were a few limitations in this study. First, the location of the monitoring site is not equal distance from the four routes. Therefore, it is possible that the background concentration was more representative for closer routes, specifically Route 4, than for other routes. Also, this initial feasibility assessment did not include all the variables that impact urban air quality. Other variables that would be important to consider are traffic volumes and fleet composition. The composition of the vehicle fleet or percentage of heavy-duty vehicles greatly impacts roadway emissions. This study compensated for omitting traffic volumes by including roadway functional classification. The known characteristics of the functional classifications imply that major roads (i.e. arterials and collectors) support more vehicles than minor roads (i.e. local roads).

In order to understand cyclist's $PM_{2.5}$ exposure over the course of a ride, this study analyzed air quality by route segments. Single second or multiple second hot spots were masked by averaging the $PM_{2.5}$ concentrations along each segment. However, these hot spots most likely could not be explained by type of cycling infrastructure. Sharp or sudden increases in $PM_{2.5}$ may have been the result of a variable not considered in this analysis.

It is also important to note that criteria pollutants other than $PM_{2.5}$ may be more representative of the relationship between air quality and type of cycling infrastructure. $PM_{2.5}$ was studied, because it can be monitored by low cost sensors. Low cost sensors for many of the other primary pollutants are far worse in performance.

Future efforts will include completing more runs and additional analysis should be conducted to determine how time of day and time of year impact cyclists' $PM_{2.5}$ exposure. This study will be expanded to include analysis of the data collected with the other sensors on the instrumented bicycle. The final result will be a complete study that defines the factors that impact cyclists' stress including pollutant exposure.

CHAPTER 5. CONCLUSIONS

The Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH) has funded air pollutant exposure studies and other similar initiatives that focus on the impact of transportation emissions on human health. The patterns found in these studies can be used to identify strategies to reduce exposure or to recommend routes or time of day for healthier travel. Through CARTEEH's research program, the Georgia Institute of Technology received funding to complete pollutant exposure studies for two unrelated, but understudied modes of transportation: paratransit transport and cycling.

The first CARTEEH project led by the Georgia Institute of Technology was an initial study to access the feasibility of using a dust aerosol spectrometer to monitor in-cabin pollutant exposure during paratransit transport. Paratransit transport provides mobility options for seniors and individuals that cannot access fixed route bus or rail services. As indicated by the literature review, there has been limited research associated with paratransit operations and there is a need for such research as the aging population of the United States becomes more reliant on paratransit.

Through monitoring the in-cabin PM exposure on *WeGo Public Transit* (Nashville, TN) and *MARTA Mobility* (Atlanta, GA), researchers found that PM concentrations increased when the doors of the paratransit bus were open, as shown by the increases in PM concentrations corresponding to stop times and (2) that elevated PM concentrations can extend beyond when the doors are closed. After the doors of the bus closed, it took substantial time (between 10 to 30 minutes) for the particles to disperse and the background

PM concentration to stabilize. Due to certain characteristics of paratransit transport, such as extended idling times and long trip durations, paratransit riders risk greater exposure to harmful pollutants than drivers/passengers of other modes of transportation. Passengers are not only subject to pollutants emitted from the paratransit buses, but also to pollutants at the requested stops. Further studies using the GRIMM® 1.109 aerosol spectrometer can be conducted to understand the health implications of PM exposure on paratransit riders.

The second CARTEEH project was an initial experiment to access the feasibility of using an instrumented bicycle equipped with low-cost air quality sensors to monitor the $PM_{2.5}$ exposure of cyclists in Atlanta, Georgia. Low-cost air quality sensors, such as the Plantower™ PMS5003 sensors, have increased the accessibility of air pollutant monitoring technology. The low cost and small size of the Plantower™ PMS5003 sensors facilitated the data collection process, because the sensors could easily be attached to the bicycle without the threat of harming an expensive piece of laboratory equipment. The use of low-cost air quality monitors allows researchers to deploy large networks of sensors and has the potential to greatly increase the quantity of collected data.

Through monitoring cyclists' $PM_{2.5}$ exposure with low-cost air quality sensors, researchers concluded that cyclists' $PM_{2.5}$ exposure was lower on designated cycling infrastructure (i.e. bike lanes and buffered bike) and on functional classifications with lower traffic volumes (i.e. minor roads). These findings are in alignment with previous research that suggested that exposure was higher near high-traffic routes and for motorists due to their proximity to motor vehicles. Land use, specifically if the cyclist was riding through a commercial area, was found to be one of the most significant indicators of cyclists' $PM_{2.5}$ exposure. This finding is significant, because the demand for bicycle infrastructure in cities is greatest in commercial areas, where desirable restaurants and businesses are present. However, cyclists' $PM_{2.5}$ exposure was found to be impacted more by meteorological variables that lead the background concentration to be higher along the entire route than the proximity to vehicles at specific points along the route.

This research will enhance the field of transportation by providing planners and engineers with information about the variation of pollutant exposure among different types of cycling infrastructure. This knowledge can be used to make more informed decisions about what types of cycling infrastructure should be implemented to provide the healthiest cycling experience. This research also provides a framework for future studies that seek to use an instrumented bicycle. Future studies should be conducted to address additional variables not used in this study. Important variables to address are traffic volumes and fleet composition, both determinants of particulate matter exposure that were not included in this study. The comprehensive findings from additional instrumented bicycle studies can be used to design better cycling infrastructure.

Both CARTEEH projects seek to better understand the hazardous pollutant exposure of different modes of transportation. The findings from these initial experiments provide transportation planners and engineers with valuable information that can be incorporated in the planning and design of transportation networks. Effective transportation networks accommodate all the needs of users including protection from harmful pollutants that negatively impact the health of passengers.

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